Correcting Market Failures in Entrepreneurial Finance*

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Abstract

To facilitate funding to small firms that are unable to access private credit, the U.S. government provides loan guarantees. We use unique administrative data on the universe of U.S. startups and their founding employees to show that startups more likely to obtain loans guaranteed by the Small Business Administration (SBA) grow more slowly than startups founded in the same year and operating in the same zip codes and industries. Consistent with a moral hazard channel, we detect underperformance only when the lending decision is fully delegated to private lenders who – given that the government assumes most of the costs of default – have limited incentives to screen and monitor borrowers. We find no such negative selection when the SBA restricts lenders' decision-making authority. To test for the role of asymmetric information, we propose a novel measure of ex-ante uncertainty of startup projects based on the intensity with which industries hire research-trained students. The negative relation between SBA lending and growth is concentrated among startups in services and manufacturing industries with more uncertain projects.

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I. Introduction

High-growth startups and young businesses are an important driver of job creation and innovation in the U.S. economy (Decker, Haltiwanger, Jarmin, and Miranda, 2014). Yet, entrepreneurs face significant hurdles to obtaining financing to found new ventures. Startups have limited hard information about their business to provide to potential financiers, such as audited financial statements. Hence credit from private sources, such as bank loans, venture capital, or private equity financing, could be prohibitively expensive (Kerr and Nanda, 2011). Absent private wealth, potential entrepreneurs may leave their projects on the table. These unborn projects can lead to missing high-growth startups, because private financiers do not internalize the social returns from the job creation and innovation of high-growth startups.

Governments can step in to address this market failure with loan guarantees, such as those provided in the U.S. through the Small Business Administration's 7(a) Loan Programs. Loan guarantees allow private financiers to transfer the risk of default to the government, and hence fund startups at affordable interest rates. However, they can also introduce new distortions (Acs, Astebro, Audretsch, and Robinson, 2016). Providing guarantees can reduce the incentives of banks to screen and monitor recipients and, particularly, to collect soft information. At the same time, banks might collect soft information for all startups, and only demand guarantees for riskier or lower-quality startups.[1] Motivational correlations from the Kauffman Firm Survey (KFS) suggest that startups that receive an SBA loan grow on average less than other startups founded in the same year, industry, and geographic area.

In this paper, we use data from the U.S. Census Bureaus' Longitudinal Business Database (LBD), full-coverage Longitudinal Employer-Household Dynamics (LEHD) program, 2010 Decennial Census, American Community Survey (ACS), and new Umetrics program together with zip-code level data on small loan financing from the Small Business Administration (SBA) to assess if and under which conditions SBA loans might introduce distortions in entrepreneurial financing.

We first replicate the KFS correlations, and find that startups with a greater likelihood of

[1] Skeptics of the SBA loan program argue that SBA loans "fund bad ideas" and amount to a subsidy to large banks. See, e.g., Hennessey, "Why the SBA Should Be Abolished," *Entrepreneur Magazine*, September 4, 2013.

receiving SBA-backed loans grow on average more slowly than similar startups founded simultaneously in the same industry and zip code. Consistent with lax screening and monitoring of guaranteed loans, we only detect underperformance when the lending decision is fully delegated to private banks. To the contrary, when the SBA restricts lenders' decision authority and the extent of the loan guarantee, we find no evidence of underperformance by startups more likely to receive SBA loans. Loan guarantees might reduce banks' incentives to screen and monitor startups. Or, if banks have an informational advantage vis-à-vis the government, they might induce banks to exploit the soft information they obtain when screening and ask the government to guarantee ex-ante riskier loans. In both cases, underperformance should be higher for startups that were harder to value ex ante. We confirm that underperformance is highest among startups that are the most difficult to value using a novel measure of ex-ante project uncertainty based on industry-level flows of research-trained students.

A key challenge for our analysis is the endogeneity of the financing decision: SBA-funded startups could differ systematically from other startups along unobservable dimensions. Because of this concern, throughout the paper we exploit variation in the likelihood startups obtain SBA financing based on the likelihood startups' employees are aware of the SBA loan-guarantee program, rather than the financing decision itself. To do so, we use the LBD to identify all new firm starts in the year 2010 and to gather firm-level information (industry, location, total employment). We then use the LEHD data to identify the founding workers of each startup, and the 2010 Decennial Census to identify the zip codes in which the workers reside.

Our main covariate is a startup-level index of the likelihood the startup received SBA financing, which is the average number of SBA loans per capita originated in the zip codes in which the startup employees resided in 2010, when the startup was founded. The rationale for this index is that employees that live in zip codes in which SBA loans are more common might be more likely aware of the program, and hence more likely to access the program.

Our baseline regressions include fixed effects for the zip codes and industries in which firms operate as well as fixed effects for the number of employees in the firm at startup. Our baseline strategy therefore does not exploit any time-invariant supply- or demand-side variation across space and across industries, or any systematic variation in the percent growth of startups due to their initial size. Thus, we compare the growth of startups of identical size operating in the same zip code and industry – and plausibly facing the same market conditions – but that differ in the exposure of their founding employees to the SBA loan program. We also control for a number of characteristics of the startups' employees and their home zip codes that might correlate both with the volume of SBA lending in that zip code and the success of the entrepreneurs' business ventures: employees' age, gender and race; the fraction of workers in the zip code who work in commercial banks; the median household income, the mean house price, and the fraction of homeowners.

We find that a one standard deviation increase in our index of the likelihood of SBA financing is associated with 1.2-percentage-point lower employment growth over the first four years. Economically, this association is higher than the effect of other proxies for entrepreneurial capita, such as the share of zip-code inhabitants that are homeowners and can extract equity from their houses.

Our baseline strategy could only provide us with a causal estimate of the effect of SBA financing on startup growth if the frequency of SBA lending in a zip code was uncorrelated with more general variation in the supply of credit to or other unobservables related to startup growth and not captured by our controls. We propose an instrumental-variable approach to attempt to isolate more fully variation in employees' awareness of the SBA loan program from more general variation in the availability of credit. This approach exploits variation in the share of residents in employees' zip codes who are employed by commercial banks, but do not work necessarily in the zip code, controlling for the share of workers in the same zip code who work in commercial banks, which are directly responsible for SBA-lending in the zip code, as well as for other forms of bank lending. We use the average share of commercial banker *residents* in employees' zip codes as an instrument for the average amount of SBA loans per capita originated in the employees' zip codes.[2] The instrument is relevant, which suggests that commercial banker neighbors in employees' personal networks might increase awareness of the SBA program above and beyond the actual origination of SBA loans where employees reside. The exclusion restriction this approach assumes states that the average share of commercial-banking residents in employees' zip codes affects the growth of their startups (in another zip code) only through the likelihood that the startups obtains an SBA loan. To assess the plausibility of this assumption, we propose the average share of commercial banker *workers* in the employees' zip codes – which is a more direct proxy for credit

[2] The share of commercial banker residents can also be interpreted as an alternative proxy for SBA loans in the zip code. Consistently, the reduced form specification gives similar results as our baseline specification.

supply in the zip codes – as a placebo instrument for the index of the likelihood of SBA financing. As expected, the placebo instrument is relevant in the first stage, consistent with it capturing variation in credit supply in the employees' zip codes. Instead, we detect no correlation between the placebo instrument and startup growth in our second-stage estimations.

That higher likelihood of SBA financing correlates with slower startup growth could reflect financing choices by the SBA acting as a lender of last resort. Or, it could reflect lax screening and monitoring by private lenders administering the loans. To distinguish these hypotheses, we exploit differences in the allocation of decision rights across two programs the SBA runs to expedite loan applications: the Preferred Lender Program (PLP) and the SBA Express Program.[3] Under the PLP, banks can obtain a guarantee for up to 85% of the loan, are fully delegated to make the credit decision, and face less stringent screening by the SBA before they are approved into the program. Under the SBA Express program, banks can obtain a guarantee for up to 50% of the loan, their decision-making authority faces restrictions, and they face a more stringent screening process to access the program. Therefore, if the moral hazard mechanism explains our baseline results, underperformance should concentrate in startups that are more likely to obtain a PLP loan, as opposed to a SBA Express loan.

To obtain variation in startups' exposure to SBA loans originated through the PLP (SBA Express program), we split startups based on whether any of their employees reside in zip codes in which we observe lending through the PLP (SBA Express program) or not. For startups with exposure to the PLP, we find a significant negative correlation between the index of likelihood of receiving SBA funding at inception and subsequent growth rates. Within the complementary sample of startups without exposure to the PLP, we do not find any significant relation. This finding is consistent with the notion that banks might reduce screening when their potential losses are insured and when their actions are not monitored, or might only ask for guarantees when financing startups of worst average quality. To corroborate this moral hazard channel, we conduct similar split-sample tests on the SBA Express subsamples. Consistent with the PLP result, the negative correlation between likelihood of SBA funding and growth is concentrated among startups whose employees are not exposed to the SBA Express program in their zip codes. Instead, if anything the correlation between SBA funding and growth is positive for startups whose

[3] These programs do not generate the universe of SBA loans. In 2010, the SBA Express program accounted for roughly 43% of all SBA loans and the PLP program for 28% of loans.

employees are exposed to the SBA program. This result suggests that the SBA loan-guarantee program per se does not attract worse-than-average startups, but might indeed solve successfully the market failure problem in entrepreneurial finance when the government restricts the lending authority of the guaranteed private lenders, and incentivizes them to screen and monitor startups by requiring non-negligible skin in the game.

The different results based on the type of SBA program available across zip codes help further reduce concerns that our results are spurious. If one worries about remaining unobservables not captured by our controls in the baseline analysis or not accounted for by the instrumental-variable strategy, such unobservables would be an issue only if they varied systematically across zip codes based on the type of SBA loan program available locally. Such systematic variation seems unlikely, because the SBA assigns the PLP and/or SBA Express lender status at the lender level, and not based on local economic conditions, and the largest SBA lenders are national commercial banks.

When firms are difficult to value, asymmetries in information about quality are more likely to arise. As long as private lenders are delegated to make financing decisions, and find screening hard-to-value startups less costly than the government, they might require guarantees for worse-than-average startups especially in the pool of hard-to-value startups. To further test for the moral hazard mechanism, we therefore exploit heterogeneity in the ex-ante uncertainty about the growth prospects of startups across industries.

To run this test, we need a proxy for the uncertainty of startup projects at the time of inception, that is, before any signals of quality like patents, trademarks, R&D or sales are produced. Moreover, because most startups belong to services industries, which tend to patent and trademark less than manufacturing industries (Lerner and Seru (2015)), we need a proxy for uncertainty of projects that is equally suitable for services and manufacturing startups. To overcome these empirical challenges, we exploit data on the flow of research-trained students into the labor force by matching data from the Umetrics program – which tracks payments to students through federal research grants at U.S. universities – to the LEHD data – which provides quarterly firm-worker matches. We compute a novel "Human Capital intensity" (HCI) Index of flows at the three-digit North American Industry Classification System (NAICS) level by dividing the fraction of students from the Umetrics data who accept jobs in the industry, scaled by the fraction of U.S. workers who work in the industry in 2010. The HCI Index captures the demand for research-trained, high-skill human capital at the industry level, as opposed to the products of research activities that started in the past, such as patents and trademarks. We use this demand to proxy for uncertainty about startup prospects: startups in industries with more demand for research-oriented employees are likely to have more uncertain growth prospects. We validate this measure by establishing a positive correlation between the HCI Index and the industry-level standard deviation of startup employment growth over various horizons.

Consistent with the moral hazard mechanism, we find that the negative correlation between the likelihood of SBA funding and employment growth among startups with more PLP exposure is largest for firms in high-HCI industries, and decreases monotonically with HCI, being smallest for startups in low-HCI industries. We find the same monotonic pattern among startups with no exposure to SBA Express loans.

Overall, our results suggest that SBA loans finance startups with systematically different growth prospects based on the design of the program, and especially on the extent to which private lenders are delegated to make the financing decision as well as on the extent of uncertainty of the startup projects.

Our paper contributes to the literature that studies the financing of early ventures, and especially the effect of credit availability on startup performance. Researchers have investigated the effects of financing from private equity funds (Kaplan and Stromberg (2008)), venture capital (Gompers (1995), Kaplan and Stromberg (2002), Ma (2016)), angel investors (Kerr, Lerner, and Schoar (2011)), commercial banks (Robb and Robinson (2014)), non-profit lenders (Fracassi et al. (2016)), government grants to R&D activities (Howell (2016)), and family and friends (Lee and Persson (2016)). We study the effect of an intervention that allows private financiers to provide credit to startups that would not obtain financing in the open market. Unlike other papers, which focus mainly on the asymmetric information problem between the entrepreneur and the financier, we analyze the implications of asymmetric information between private financiers and the government and ask whether the government can provide guarantees to allow the financing of startups without inducing negative selection of startups into the program.

We also contribute to the literature on the design and effects of loan-guarantee programs. Beck et al. (2008) and Gozzi and Schmukler (2015) describe the institutional features of several loan-guarantee programs around the world. Both contributions emphasize the need to better understand the relative incentives loan guarantees create, not only between potential entrepreneurs and the government, but also between private lenders and the government. We build on earlier studies of the effects of loan guarantees on firm-level and aggregate outcomes around the world. Lelarge et al. (2010) and Bach (2014) study a loan-guarantee program in France. Cahn et al. (2016) analyze an intervention on loan guarantees by the French government during the recent financial crisis. Mullins and Toro (2016) study the effect of loan guarantees in a regression discontinuity design in Chile. de Blasio et al. (2014) study a loan-guarantee program in Italy. Most directly related to our work, Brown and Earle (2017) study the effect of SBA loans on employment in US businesses. We differ from existing papers by focusing on the role of loan guarantees in funding startups. The moral hazard channel we study is specific of startups as opposed to existing small businesses, for which verifiable, hard information is more abundant.

Finally, our paper fits into the literature that studies the effects of government intervention in the lending market. Smith (1983) and Gale (1990) model the effects of government lending policies in the presence of credit rationing induced by asymmetric information between borrowers and private lenders. Philippon and Skreta (2012) study optimal governmental intervention in the form of debt guarantees to financial institutions when participating in the government program carries a stigma. Empirically, Shleifer (1998) argues that the scope of government in a country with good contract enforcement should be limited to situations in which soft incentives are extremely valuable and competition is limited. La Porta, Lopez-de Silanes, and Shleifer (2002) and Sapienza (2004) study the effect of government ownership on bank lending to private corporations using aggregate and loan-level data and find that government intervention in lending varies systematically around election cycles. Recently, Acs, Astebro, Audretsch, and Robinson (2016) provide a negative viewpoint on the effectiveness of governmental policies aimed at fostering entrepreneurship. We contribute to this line of research by highlighting the allocation of the decision-making authority between the government and private lenders for the effectiveness of government intervention in private lending markets.

II. Institutional Setting

Governments around the world provide loan guarantees to support the extension of credit to small businesses.[4] In this paper, we focus on loan guarantees the SBA provides to lenders to

[4] For instance, see Lelarge et al. (2010), Bach (2014), and Cahn et al. (2016) for two French programs, Mullins and

support the extension of credit to US startups under the 7(a) program, which is the largest SBA loan program. We base our discussion of the 7(a) program and subprograms on the SBA Standard Operating Procedure (SOP) number 50 10 5(C), which was approved in 2010, the year to which our analysis refers.[5]

SBA loans provide banks with a guarantee in exchange for a guaranty fee lenders pay at the time the guarantee application is accepted. Loans in the programs we study have a maximal nominal amount of $5 million. The SBA guarantees from a minimum of 50% to a maximum of 85% of the nominal loan amount, based on the amount and other considerations at the discretion of the SBA. Banks can access the loan guarantee program as long as they charge borrowers an interest rate not higher than the maximal interest rate the SBA establishes for the loan.

Although this paper focuses on startup financing, the SBA program provides loans to firms of any age. Borrowing firms can only employ the funds obtained through SBA loans for six uses: (i) to fund startup costs; (ii) to purchase new land (including construction costs); (iii) to repair existing capital; (iv) to purchase or expand an existing business; (v) to refinance existing debt; and (vi) to purchase machinery, furniture, fixtures, supplies or materials. Borrowing firms' eligibility is based on five criteria: (i) they must be an operating business; (ii) they must be organized for-profit; (iii) they must be located in the United States (includes territories and possessions); (iv) they must be "small"[6]; and (v) they must demonstrate a need for the desired credit. The SBA requires borrowers to be unable to obtain funds from other private sources. To ensure fulfillment, the SBA requires lenders that ask for SBA loan guarantees to pass a Credit Elsewhere Test. This test consists of a statement to be signed by the lender, which states that without the participation of SBA to the extent for which it is applied, they would not be willing to make the loan, and, in their opinion, the financial assistance is not otherwise available on reasonable terms. Lenders must accompany the signed statement with a thorough explanation of why reasonable terms cannot be applied to the loan.

To test for the moral hazard mechanism, we focus on two subprograms through which the SBA provides expedited decisions on loan applications: the PLP and the SBA Express Program.

Toro (2016) for Chile, de Blasio et al. (2014) for Italy, and Brown and Earle (2017) for the United States.

[5] The official document in .pdf format is available online at the following address: https://www.sba.gov/sites/default/files/sops/serv_sops_50105c_loan_0.pdf

[6] Every year, the SBA sets size thresholds that vary by industry based on one or more of the following quantities: assets, average annual receipts, and employment. The 2016 definitions of small sized by NAICS industries can be found at the following address: https://www.sba.gov/sites/default/ les/ les/Size Standards Table.pdf.

Both programs provide a guaranteed fast-track processing procedure that lasts at most 36 hours. Table A.1 in the Online Appendix provides a comprehensive comparative analysis of the different features across the two programs which are crucial to our analysis. First, the two programs differ in the extent of the loan guarantee. The PLP allows for a guarantee up to 85% of the amount of the loan, whereas the SBA Express caps the guarantee to 50% of the amount of the loan. The incentives to screen and monitor borrowers are therefore lower in the PLP. Second, the credit decision is fully delegated to the PLP lender with a generic request to run a complete and thorough credit analysis of the applicant. For the SBA Express lender, delegation is restricted by additional provisions. For instance, the lender needs to use the same methods to screen borrowers as they do for non-SBA guaranteed commercial loans, it needs to document all the statistical analysis it performs and why the methods are predictive of loan performance, and they need to verify the collateral in case they require any collateral for their non-SBA loans, and hence require it for SBA loan applicants too. Third, lenders face relevant differences in the screening procedure to obtain their status as SBA lenders. The screening process for the PLP allows lenders to provide several crucial pieces information on their own, such as the experience and ability of the loan officer in charge of PLP loans. In the SBA Express program, the Lender Transaction Team (LTT) at the SBA collects all the relevant information on their own. Moreover, the renewal of PLP lender status is quicker, and the SBA allows for temporary extension of the PLP lender status in case it does not conclude the renewal process by the deadline, whereas extension is not allowed for SBA Express lender status. Overall, the incentives to screen and monitor borrowers appear to be lower for PLP lenders than for SBA Express lenders. If the reason for underperformance is lax screening of borrowers, or lax monitoring after the loan is approved, then it should arise more in the PLP than in the SBA Express program.

III. Data

To conduct our analysis, we use several data research databases available from the U.S. Census Bureau. We use the Longitudinal Business Database (LBD) to identify startups of new employer firms. The LBD includes all non-farm establishments in the U.S. and contains information on plant ownership, location, status (active or inactive), industry, aggregate employment, and total payroll, reported at the end of the first quarter of each calendar year (March

12). We identify startups as businesses in their first year of activity that report at most 10 employees. We impose the latter restriction to minimize measurement error, both in the classification of the firm as a startup and in the identification of the firms' founding employees. However, it is not crucial for our results. We use the aggregate employment and payroll data to calculate growth rates for each startup over horizons of 1, 2, 3, and 4 years.

We use data from the full-coverage Longitudinal Employer-Household Dynamics (LEHD) program to identify all of the employees who worked for each startup firm at any time during its first year of operation. The LEHD data are a worker-firm matched quarterly panel that includes all employees in U.S. establishments for whom the employer pays an unemployment insurance fee. The data cover more than 96% of civilian jobs in the U.S and include information on wages and basic demographic characteristics (age, gender, race). The LEHD data is linkable to the LBD using federal tax identifiers (employer identification numbers, or EINs). When merging the two datasets, we require that there be no more than a one year gap between the years in which we first observe the firm in the two research databases. Though it is not generally possible to link workers to specific LBD establishments within a state and industry, our focus on single-establishment startups allows us to do so. This unique match across the two research datasets allow us to infer worker location with a higher degree of confidence than would otherwise be possible. The LEHD data do not identify firm founders. In our baseline specifications, we define any workers who we observe at the startup during its first year of operations and who are present for at least four of the firm's first five quarters as founding employees.

Our empirical strategy exploits variation across zip codes in which employees reside. To identify employees' zip codes, we match the set of startup employees to the 2010 Decennial Census. We impose two additional restrictions to minimize measurement error in the identification of employees' residences. First, we limit our sample only to startups that are founded in 2010, because we have no source of residential information for other years. Second, we eliminate cases in which the zip code an employee reports in the Decennial Census is more than 100 miles from the zip code in which the firm operates.[7]

Having identified founding employees' home zip codes, we retrieve measures of zip-code-level characteristics from the 2010 American Community Survey (ACS). We use the ACS to

[7] This restriction should also eliminate cases in which multi-unit firms could be misclassified as single-unit firms due to changes that occur between Census surveys.

measure median household income, the value of the housing stock, the fraction of residents that are homeowners, and the share of residents that are employed by commercial banks (potentially in other zip codes). We also use the LBD to calculate the share of employees in each zip code who work in commercial banks (regardless of where they reside). Finally, we retrieve from the SBA information on the characteristics of SBA loans originated in 2010 in each zip code that appears in our data as an employee residence.

In Table 1, we report summary statistics of the data. In Panel A, we report the geographic distribution of startups across Census divisions. Our study incudes startups and their employees in all U.S. states, without any geographic restrictions. The most represented Census divisions are the South Atlantic – which includes Delaware, Maryland, Virginia, West Virginia, the District of Columbia, North Carolina, South Carolina, Georgia, and Florida – and the Pacific – which includes California, Oregon, and Washington. Roughly 20% of startups are founded in the Northeast, which is comprised of the Middle Atlantic (New York, New Jersey, and Pennsylvania) and New England.

In Panel B, we describe the distribution of startups across two-digit NAICS industries. The most represented industries are Healthcare and Social Assistance (NAICS 62), Professional, Scientific, and Technical Services (NAICS 54), and Accommodation and Food Services (NAICS 72). Thus, our sample contains startups in both services and manufacturing industries, as well as low- and high-tech startups. We exploit this heterogeneity later in the paper to capture differences in the ease with which financiers can evaluate startup value.

In Panel C, we summarize the characteristics of founding employees. We report individual characteristics of the founding employees – including age, race, and gender – as well as characteristics of the zip codes in which founding employees reside. 49% of the founding employees in our sample are women. The average age is 39. Roughly 6% of founding employees are African American and 11% are Asian. The average founding employee works for a startup with 3.3 initial employees and resides in a zip code in which 66% of residents are homeowners, the mean home value is roughly $250,000, and median household income is roughly $71,000.

IV. SBA Loan Guarantees and Startup Growth

Our goal is to test whether loan guarantees that allow lenders to offload the risk of the loans they make to new businesses create distortions in startup lending. For instance, lenders might be more likely to reduce screening and monitoring of loan applicants. Or, if they screen startups, they might demand guarantees only for startups of lower-than-average quality. In these cases, we would observe a negative relation between SBA lending and startup performance.

To explore the sign of this relation, we first consider the Kauffman Firm Survey (KFS), which covers a panel of 4,928 U.S. startups founded in 2004. The KFS is the first large-scale data set that covers startups since their inception, and collects detailed information about all their sources of financing as well as a large set of outcomes (Robb and Robinson (2014)). In particular, the KFS allows us to observe whether startups received a business loan guaranteed by the U.S. government in the year of inception, as well as employment growth as a measure of performance.[8] The top graph of Figure 1 plots the coefficients and related 95% confidence intervals when estimating a set of linear specifications by ordinary least squares. Each histogram refers to a different equation, in which the left-hand-side includes the percent employment growth of the startup in year 1, 2, 3, and 4 after inception. The time period is therefore between 2004 and 2008. The right-hand-side is the same across all specifications. It includes a dummy variable that equals 1 if the startup received a government-guaranteed business loan at inception – the histogram refers to the coefficient associated with this covariate – as well as the logarithm of the number of employees at inception, a set of demographic characteristics of the principal owner of the startup (female dummy, African-American dummy, Asian dummy), a fixed effect for the census region in which the startup was founded, and a fixed effect for the NAICS 2 industry to which the startup belongs. Table A.2 reports the coefficients and t-stats associated to all controls and the number of observations for each specification in tabular form.

Across all horizons, being funded with a government-guaranteed loan is negatively associated with employment growth. We can reject the null that the coefficient of interest equals zero in year 1 and year 2 at the 5% and 10% level of significance, respectively. Despite their magnitude, we cannot reject the null that the coefficients equal zero in year 3 and 4, for which our estimates are very imprecise. We see this negative association between government-guaranteed loans and startup employment growth as motivational evidence for our analysis, but the KFS sample has a set of fatal issues that do not allow conducting further analysis. The main problem is that, once we exclude sole proprietorships, startups that did not respond to the government

[8] Other proxies for performance, such as growth in sales or profits/losses over time, are only available for a subset of KFS startups.

financing question, and startups whose employment is not recorded every year before they die, we are left with only 1,057 startups in 2004. Because startups with government-guaranteed loans constitute about 2.5% of the sample each year, and the rate of survival of startups is lower than that of established firms, the analysis only includes between 12 and 22 startups with government-guaranteed loans across specifications. The paucity of this sample makes it impossible not only to perform reliable statistical inference, but also to propose any tests for the moral hazard channel we described above.

To overcome this issue, we move on to analyze our confidential Census Bureau sample, which includes the universe of startups founded in the U.S. in 2010, and for which we can observe employment growth and employees' characteristics up to 2014. The main drawback of this sample is that the Census Bureau does not allow us to import firm-level data on SBA loans as part of our project. Our data on SBA loan guarantees is available at the 5-digit zip-code level. Note that a regression of employment growth on whether the startup obtained a SBA loan at inception would be plagued by a large set of endogeneity concerns, and we would anyway need a strategy to isolate a source of variation in the prevalence of SBA financing that is exogenous to the financing decision itself. At the same time, we cannot estimate this endogenous regression in the Census Bureau sample.

We choose zip codes as the unit of analysis rather than a larger partition such as MSA or county, because different locations within the same MSA or county can have different local demand and economic shocks (Kremer, 1997), different levels of gentrification and shocks to the value of housing (Guerrieri, Hartley, and Hurst, 2013), and different supplies of local financial services (Nguyen, 2016). All of these dimensions have been shown to be important to finance new venture creation.

A possible approach to test whether SBA loans affect startup growth is to regress the growth of startups in a zip code on the amount of SBA loans per capita, controlling for zip-code level observable characteristics. However, even with an extensive set of controls for individual and market characteristics, time-invariant unobservable factors at the zip code level could affect both startup growth and the availability of SBA loans, making the regression results difficult to interpret. A zip-code fixed effect would absorb these unobservables, but would also absorb all of the variation in our independent variable of interest. Thus, for our baseline analysis, we need a source of variation in the likelihood of obtaining an SBA loan across startups operating in the same zip code, and using zip-code-level information on SBA loans. To address this empirical challenge, we exploit variation in the prevalence of SBA-guaranteed loans across the zip codes in which the founding employees of the startups reside. The rationale is that this variation might capture the likelihood that founding employees are aware of the SBA program. Employees that reside in zip codes in which more SBA loans per capita are originated might be more likely to interact with neighbors who obtained such loans, or to be exposed to advertisement of the SBA program. Higher awareness would increase the likelihood the startup (operating in a different zip code) exploits the program for financing.

We define an index of the likelihood of obtaining an SBA loan. The index is the average number of SBA loans per capita originated across the zip codes in which the startup employees reside. We observe such variation in the majority of startups in our sample, because about 70% of the startups' employees reside in a zip code that is different from the one in which their startup operates.

An important concern with the variation we exploit to construct the index is that startups' employees sort into residential zip codes based on unobservable characteristics that affect both the local availability of SBA loans and the quality of employees' entrepreneurial ideas and ventures. In particular, both variables could be determined by the local supply of financial services, or by the availability of private wealth that founding employees could exploit to finance the operations of their startups. To alleviate these concerns, our baseline analysis controls directly for the average supply of commercial banking services in the employees' zip codes, median household income, mean house prices, the average share of zip-code residents that own their house, as well as average characteristics of the startups' workforce such as the average age, share of women, share of African-American, and share of Asians. In section IV.C, we propose an instrumental-variable strategy to isolate explicitly variation in employees' awareness of the SBA loan program from variation in the availability of bank credit in the zip codes in which they reside.

IV.A. Startup Employment Growth

In our baseline analysis, we compare the employment growth of startups that operate in the same location and in the same industry, and hence are exposed to the same local demand, local economic shocks, and industry-level unobserved characteristics. We focus on employment growth as our outcome variable because it is arguably the best measure of the success of startup firms. Newly-created ventures do employ personnel from their inception, whereas they often have no sales and do not produce revenues until later in their life cycle. Thus, it is difficult to measure initial growth using real output outcomes that are meaningful for older firms. Note there is substantial variation in employment growth rates across startup firms. For example, Decker et al. (2014) find that most startups grow little or die over time, but that the employment created by high-growth startups is higher than the employment destroyed by exiting startups.

We estimate the following linear specification, in which the unit of observation is a startup:

$$\begin{aligned} Startup\ Employment\ Growth_{fzk,2010\to t} &= \alpha + \beta Index\ SBA\ Loan_{fzk,2010} + \boldsymbol{X}'_{fzk,2010}\boldsymbol{\gamma} + \boldsymbol{D}'_{fzk,2010}\boldsymbol{\delta} + \eta_f + \eta_z + \eta_k \\ &+ \epsilon_{fzkt}, \end{aligned} \tag{1}$$

where startup *f* operates in zip code *z* and industry *k*. $Startup\ Employment\ Growth_{fzk,2010\to t}$ is the natural logarithm of the cumulative employment growth of startup *f* from the founding year (2010) until the end of year *t* of activity. $Index\ SBA\ Loan_{fzk,2010}$ is the index of the likelihood the firm *f* obtained an SBA loan in 2010, that is, the average number of SBA loans per capita in the zip codes in which the startups' founding employees reside.[11] $\boldsymbol{X}'_{fzk,2010}$ is a set of average demographic characteristics of startups' founding employees, which include gender, age, and race. $\boldsymbol{D}'_{fzk,2010}$ is a set of average characteristics of the zip codes in which founding employees resided in 2010, which includes the logarithm of the median household income, the logarithm of the mean house price, the percent of residents that own their house, and the fraction of workers in the zip code employed in commercial banking. η_f is a fixed effect for the number of employees in the startup in 2010.[12] We include fixed effects for startup size rather than a continuous control because changes in employment are discrete and the set of possible outcomes differs depending on the level of employment (particularly when the level of employment is low). However, our results are not sensitive to this choice. η_z is a fixed effect for the 5-digit zip code in which the startup operates

[11] We define the set of founding employees to be all employees who we observe at the startup during its first year and who stay at the startup for at least four of its first five quarters. Note that all startups in our sample must survive for at least five quarters so that we can observe both a startup employment level and an employment level one year in the future to calculate one-year growth rates. Thus, this restriction imposes no additional constraints on the sample.
[12] Specifically, we include a fixed effect for the total number of employees reported in the LBD in the first year the firm appears in the database.

and η_k is a fixed effect for the two-digit NAICS industry in which the startup operates. Because the growth rates of startups operating in the same local markets are unlikely to be independent, we cluster standard errors at the level of the zip code in which startups operate.

In Table 2, we report the results of estimating Equation (1) by ordinary least squares (OLS) using cumulative employment growth until the end of year 1 (column (1)), year 2 (column (2)), year 3 (column (3)), and year 4 (column (4)). We find that the employment of startups with a higher likelihood of receiving SBA financing grows significantly slower that the employment of startups of the same initial size operating in the same zip codes and same industries. A one-standard-deviation higher index is associated with a 0.8-percentage-point lower growth rate over the first year of startup operations. The magnitude of the association increases over longer horizons, with a maximum value of 1.23 percentage points over a four-year horizon.

Note that the OLS specifications are likely to estimate downward-biased coefficients for at least two reasons. First, the *Index of SBA loan* might capture the availability of other forms of capital not controlled by our independent variables, and the availability of capital is generally a positive determinant of startup growth. Second, our index is a continuous variable that proxies for the likelihood the startup has a SBA loan. But only a small fraction of startups that have a positive likelihood of obtaining an SBA loan do indeed ask for and/or obtain an SBA loan. Our "treated" group therefore also includes startups that did not ask for or received SBA loans, which attenuates the size of the estimated coefficients. We confirm the conjecture that OLS estimates are downward biased in the instrumental-variable analysis described below, which aims to isolate more fully founders' awareness of the SBA program from the availability of capital in the zip code.

One could assess the economic magnitude of the effects by comparing the coefficient estimates on the independent variables. Making generalizations based on comparisons to the other zip-code-level characteristics in the regressions is challenging, because the effects of the other zip code characteristics are both more variable across specifications and less statistically reliable than the effects of SBA loans per capita. This fact suggests that after controlling for startups' zip code and industry, these important determinants of firm financing do not have incremental explanatory value for startup growth. Prior research finds that equity extraction from housing is an important source of financing for entrepreneurs (Schmalz et al. (2017)). Consistent with this channel, we find that the prevalence of home ownership in founders' home zip codes predicts startup growth positively. A one-standard-deviation increase in the average share of homeowners (0.17) in the employees' zip codes is associated with 0.99 percentage points higher startup employment growth. The magnitude of the effect typically appears to be lower than the association of the likelihood of SBA loans with employment growth. The incremental effects of home values (and household income) appear to be negative, though imprecisely estimated.[14]

Finally, we note that average founding employee demographics have significant predictive power for startup growth. Startups founded by women, younger employees, and African Americans tend to grow more than other startups across the four-year horizon. Startups founded by Asians appear to grow less. Given that we observe strong demographic patterns, a possible concern is that our index picks up the effect of an omitted control for entrepreneur quality. We experiment with additional controls for entrepreneur demographics using information available from the LEHD data. In particular, we include additional controls for the founding employees' last observed quarterly wages prior to working in the startup as well as an indicator variable for whether the employees were likely to have been laid off from her last job and a series of indicator variables that capture employees' highest education levels.[15] Though we lose some observations due to missing data, we find, if anything, that our estimates are stronger when we add these additional controls, increasing our confidence that the index of SBA loans is not capturing important omitted entrepreneur characteristics.

IV.B. Startup Survival

Though arguably the easiest metric to observe and compare across startups, employment growth is not a perfect signal of startup success. We can only measure employment growth conditional on startups surviving until the end of the first, second, third, and fourth years of operation. Differences in employment growth can be difficult to interpret if there are also differences in survival rates across startups. We know that exit rates among startup firms are high (Decker et al. (2014)). Then, by staying smaller than other startups, SBA-loan-backed startups could be more likely to survive over time. If so, it would be hard to assess whether low-growth, but high-survival startups are "worse" performers than high-growth low-survival startups. Moreover, assuming the worst startups are the ones that exit, a comparison of employment growth

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[14] One possible explanation for this pattern would be that private wealth allows entrepreneurs to finance the creation of worse startups than other sources of finance, but does not ease ongoing financial constraints over time.

[15] We classify an employee as likely to have been laid off if employment in her former employer decreased by twenty percent or more at the time she left the firm. We are generally cautious in using the information on education available in the LEHD data because it is imputed the vast majority of cases.

between startups that conditions on survival would be biased towards finding higher growth rates among startups that are not SBA-backed. Alternatively, startups backed by SBA loans could in fact be more successful and grow faster than other startups on average, and for this reason be more likely to be acquired by incumbents (Wang, 2016). If so, we would observe lower growth rates among surviving independent startups backed by SBA loans compared to other startups, even though the most successful startups used SBA loans to begin their activities.

To assess the extent to which these concerns are relevant in our setting, we estimate the following regression by ordinary least squares:

$$Startup\ Survival_{fzk,t} = \alpha + \beta Index\ SBA\ Loan_{fzk,2010} + \boldsymbol{X}'_{fzk,2010}\boldsymbol{\gamma} + \boldsymbol{D}'_{fzk,2010}\boldsymbol{\delta} \quad (2)$$
$$\eta_f + \eta_z + \eta_k + \epsilon_{fzk,t},$$

where $Startup\ Survival_{fzk,t}$ is a dummy variable that equals 1 if the startup survived in year t, and zero otherwise. All other covariates are defined as in Equation (1). Unlike our estimates of Equation (1), here the composition of the sample does not change with the time horizon.

We present the results in Table 3. We fail to reject the null that startups whose founding employees reside in zip codes with more SBA lending per capita are as likely to survive as other startups. Thus, the evidence suggests that differences in startup exit rates (either successfully via merger or unsuccessfully via liquidation) do not cloud the interpretation of difference in employment growth rates in our setting.

IV.C. Instrumental-variable Strategy

A challenge for the interpretation of our baseline employment growth results is the possibility that unobservable characteristics of the zip codes in which the founding employees reside could correlate with both the prevalence of SBA loans in the founding employees' zip codes and with the performance of their startups. For example, SBA lending in a zip code could correlate with variation in the supply of bank credit not captured by our control for the prevalence of commercial banking in the zip code (and our other controls for wealth, income, and employee traits).

To address this challenge, we propose an instrumental-variable strategy to isolate the variation in awareness of the SBA program from variation in credit supply and demand. We instrument for our index of SBA loans in Equation (1) with the average fraction of residents in the employees' zip codes who are employed in commercial banking (NAICS 52), who do not necessarily work in the zip code. The idea is that interactions with neighbors who work in commercial banking increase the likelihood that a startup employee is aware of the SBA loan program. Recall that one of our controls in Equation (1) is the fraction of workers employed in the zip code who work in commercial banking. Thus, the coefficient estimate on the fraction of commercial banker residents captures the effects of having bankers in the founders' residential networks distinctly from the effect of living in a zip code that has a lot of commercial banks.

In Table 4, we first report the results of estimating the reduced form equation, which regresses employment growth directly on the instrument, in a specification similar to Equation (1). Overall, the results are remarkably similar to our baseline results from Table 2.

The instrumental-variable implementation tightens the link between the fraction of commercial banker residents in founders' zip codes and the effect of SBA lending on startup growth in two ways. First, we explicitly confirm the link between local network ties to commercial bankers and local SBA lending in the first stage (i.e., the relevance of local commercial bankers to SBA lending). Second, we isolate this source of variation in the likelihood of SBA loans and confirm that it predicts lower startup employment growth in the second stage. Given our control for commercial bankers who work in the founding employees' zip codes, a significant finding in the second stage requires a real distinction between commercial bankers who merely work in the founding employees' home zip codes and commercial bankers who reside in the zip code (i.e., it cannot reflect dimensions related to the supply of commercial banking services in the zip code). The most natural reason for such a distinction seems that founding employees are more likely to interact with commercial banker residents through neighborhood networks and, hence, to learn about the SBA program.

We estimate the following system of linear equations using two-stage least squares:

$$Index\ SBA\ Loan_{fzk,2010} = \alpha + \beta Avg.Pct.ResidentsBanking_{fzk,2010t} + \boldsymbol{X}'_{fzk,2010}\boldsymbol{\gamma} + \boldsymbol{D}'_{\boldsymbol{fzo},\mathbf{2010}}\boldsymbol{\delta} + \eta_f + \eta_z + \eta_k + \epsilon_{fzk,2010}. \tag{3}$$

$$Startup\ Employment\ Growth_{fzk,2010\to t} = \qquad (4)$$
$$\alpha + \beta \widehat{SBA\ Loans}_t + \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \boldsymbol{D}'_t\boldsymbol{\delta} + \eta_f + \eta_z + \eta_k + \epsilon_{itfzk},$$

Equation (3) is the first stage. We predict the firm-level index of SBA loans with the average fraction of employees' zip-code residents employed in commercial banking. All controls are the same as in Equation (1). In particular, we continue to include the fraction of zip-code workers in commercial banking. Equation (4) is the second stage. It corresponds to Equation (1) except that we use only variation in the index of SBA loan that is predicted by the instrument in the first stage to identify β.

We report the results of estimating Equation (3) in Panel A of Table 5. At all four time horizons of employment growth, we find that the instrument positively predicts SBA loans per capita in the zip code, conditional on the other controls and fixed effects.[16] In all cases, the coefficient on the instrument is statistically significant at the 1% level, with t-statistics exceeding 20. Economically, a one-standard-deviation increase in the share of residents of the zip code employed in commercial banking is associated with an index of SBA loans that is roughly 12% of a standard deviation higher. The high first-stage F-statistics suggest that the instrument is unlikely to be weak.

The validity of the instrument rests on the assumption that having more neighbors employed in commercial banking only affects the growth of founding employees' startups – which operate in a different zip code – through its effect on the likelihood the startups obtained an SBA loan. Ultimately, this exclusion criterion is untestable. However, to the degree that we can identify challenges to the exclusion criterion, they appear to go in the wrong direction to generate a negative correlation between the likelihood of SBA-backed lending and employment growth. For example, neighbors working in commercial banking might provide employees with financial advice on how to improve the startups' operations, which would tend to increase startups' employment growth. Alternatively, they might provide advice on the financial sustainability of business plans that prevents potential entrepreneurs from founding low-quality businesses in the first place (Lerner and Malmendier (2013)), an effect that again would generate a positive correlation with startup

[16] The regressions differ over different time horizons only because the samples differ as dictated by the second stage regressions. SBA loans per capita in the zip code are always measured in 2010.

employment growth. Or, neighbors in commercial banking might be aware of other private sources of financing available to the startups outside of the SBA program. Interacting with more neighbors employed in commercial banking should then be beneficial to the growth of founding employees' startups.

In Panel B of Table 5, we report the results for estimating Equation (4). At the end of the first year of activity, a one-standard-deviation higher share of (instrumented) average SBA loans per capita in the employees' zip codes reduces the startup employment growth by roughly 9 percentage points. At the four year horizon, the magnitude of the effect grows to 14.3 percentage points. As expected, the size of the effect is substantially larger than the baseline OLS counterparts in Table 2, which is consistent with the likely downward bias in the OLS estimates we discussed above.

As a final step to assess the validity of our instrumental-variable estimates, we construct a placebo test. If personal interactions with commercial-banking neighbors are important, as opposed to the supply of financial services in the zip code, then the share of zip-code workers in commercial banking – who do not necessarily reside in the zip code – should be unrelated to the growth of founding employees' startups in another zip code. To test whether this is the case, we use the average share of zip-code workers in commercial banking as a placebo instrument for the availability of SBA loans in the founding employees' zip codes, without controlling for the share of residents employed in commercial banking.

We report the results of this placebo test in Table 6. We document a strong first stage that is consistent with the supply-side interpretation of the placebo instrument. That is, a higher average share of zip-code workers in commercial banking is a positive and significant predictor of the availability of SBA loans in the zip code. However, the variation in SBA loans per capita in the founding employees' zip codes predicted by the placebo instrument is unrelated to startups' employment growth in the second stage. In fact, over the four-year horizon, the relation is actually positive, though insignificant. Moreover, the placebo instrument is not significantly associated with startups' employment growth in the reduced form specification.

V. The Moral Hazard Mechanism

Thus far, we have established that, on average, startups whose founding employees are more likely to obtain SBA loans grow less than otherwise similar startups. This result is consistent with a moral hazard problem under which private lenders, who make the decision to extend credit under the SBA program, but do not bear the full costs of default, decline to adequately screen and monitor entrepreneurs who receive guaranteed loans under the program. In this Section, we conduct two tests of the hypothesis that the moral hazard mechanism induces the negative relation between SBA financing and startup growth.

Our tests exploit variation in the extensive margin of moral hazard – whether there is scope for moral hazard to arise in our setting – and in the intensive margin – conditional on there being scope for moral hazard, whether the effects are stronger for startups for which the moral hazard problem should be more severe.

V.A. Extensive Margin of Moral Hazard

Our first test exploits institutional differences between two subprograms of the SBA 7(a) program designed to expedite the loan application process. In all cases, SBA loan guarantees shift much of the cost of loan defaults from the lender to the government. As discussed in section II, the Preferred Lender Program (PLP) gives lenders a guarantee of up to 85% of the loan, fully delegates banks in the credit decision, and performs a screening of banks to obtain PLP status that is less strict compared to the screening SBA Express program lenders face. Instead, the guarantee for SBA Express lenders is up to 50% of the loan, and the SBA restricts lenders' decision-making authority in the SBA Express program. Therefore, the incentives to screen borrowers before originating a loan and to monitor their repayment ability after the loan is originated are lower for the PLP than for the SBA Express program.. To test for moral hazard, then, we compare the difference between the effect of SBA loans on startup employment growth in the two programs. If a moral hazard problem causes negative selection into SBA loans, our baseline effect should be driven by loans extended through the Preferred Lender Program, in which there is higher scope for moral hazard on the side of banks. If we do not find a negative correlation between SBA lending and employment growth within the SBA Express program (in which incentives are more aligned), it would confirm the ability of the SBA to reduce moral hazard incentives through program design. Importantly, any differences in the associations of SBA loans and employment growth across the programs would also further validate our interpretation of the evidence in Section IV, because there is no obvious reason why omitted factors that could confound our analysis of the effect of

SBA lending on average would vary with the differences across the two SBA subprograms.

We perform our test in two steps. First, we estimate Equation (1) for startups whose initial employees who reside in zip codes in which at least one loan was originated in the PLP in 2010 and zip codes in which no such loans were originated. Building on the logic of the tests in Section IV, entrepreneurs whose exposure to the SBA loan program comes from interacting with borrowers in the PLP are more likely to be aware of and to exploit this particular lending program. We report the results for this test in Table 7. In Panel A, we present the results for the subsample of founding employees for whom exposure to the SBA program is likely to be through the PLP. As predicted by the moral hazard mechanism, we find in this subsample a strong negative relation between the likelihood of receiving an SBA loan and startup employment growth, similar to our baseline results in Table 2 except for the fact that the size of the estimated coefficients is more than double than the size of the average baseline association. In Panel B, we present the results for the subsample of employees who live in zip codes in which exposure to the SBA program does not come from loans in the PLP (i.e., in which we observe no PLP loans in 2010). Given the SBA's involvement as either the decision-maker or monitor, we do not expect the moral hazard channel to operate in this sample. And, as predicted, we do not observe any significant relation between the likelihood of receiving an SBA loan and startup employment growth in this subsample.

We also perform parallel tests for the set of founding employees with and without exposure to the SBA Express Program in the zip codes in which they live. Again, we estimate Equation (1) separately in each subsample: once for startups with founding employees residing in zip codes where no SBA loans in the SBA Express Program were originated in 2010, and separately in zip codes where at least one such loan was originated. We present the results for this test in Table 8. In Panel A, we report the results on the subsample of startups with founding employees who live in zip codes in which loans from the SBA Express Program were originated in 2010. For lenders within the SBA Express Program, the program design produces higher incentives to screen and monitor borrowers. In this subsample, the employment growth of startups that are more likely to receive SBA-backed loans is higher than the growth of otherwise similar startups. Thus, where incentives are set against moral hazard be less likely to arise, moral hazard does not arise. If anything, the program selects startups that perform better going forward. In Panel B, we report the results on the subsample of founding employees who live in zip codes in which no loans were originated through the SBA Express Program. Any SBA loans in these zip codes, then, either occurred through the PLP or through the non-expedited procedure. In the former case, loans are screened by private lenders and, in the latter, by both the private lender and SBA. Unsurprisingly, our baseline result – a negative correlation between the likelihood of receiving an SBA loan and startup employment growth – appear in this subsample.

Though it seems unlikely given its objective that these results are due to the SBA picking winners relative to private market loans, they could arise from entrepreneurs self-financing particularly poor projects. If so, our finding that projects that are likely to be SBA funded have the worst average growth rates (Table 2) suggests an even stronger adverse impact of lax screening.

On a side note, the differential results based on the type of SBA programs available across zip codes also helps further reduce concerns that our baseline results are spurious. If one worries about potential unobservables not captured by our controls in the baseline analysis or not accounted for by the instrumental-variable strategy, such unobservables would be an issue only if they varied systematically across zip codes based on the types of SBA program available locally. This systematic variation seems unlikely, because the SBA assigns the PLP and/or SBA Express lender status at the lender level, and not based on local economic conditions, and the largest SBA lenders are national commercial banks.

V.B. Intensive Margin of Moral Hazard

Our second test exploits variation across startups in the information frictions that allow moral hazard to arise. The moral hazard problem should be more relevant for startups with more uncertain projects, which are harder to value ex ante. Such projects require more careful screening to determine project quality. Moreover, in the instance that the government delegates this task to private lenders (i.e., in the PLP), there is more opacity as to whether such screening has occurred. If the screening has occurred, full delegation of the credit decision might incentivize PLP lenders to require guarantees for the startups they expect to perform worse. We therefore test whether the negative correlation of SBA-backed loans with employment growth in instances in which decision rights are delegated to private lenders is more relevant for startups that are harder to value ex ante.

To obtain variation in how hard it is to value startups ex ante, we exploit data from the Umetrics project, a novel project at the Census Bureau that collects information on all the individuals who receive money from federal grants to conduct research at US universities.[18] We track the industries in which all graduate and undergraduate students on research grants accept jobs following graduation. We use the flows to construct a measure of demand for highly skilled, research-trained employees in each industry, which we call the Human Capital Intensity index (HCI). We compute the HCI index for each three-digit NAICS industry as the share of Umetrics students placing in the industry scaled by the share of all U.S. employees in the industry:

$$HCI\ Index = \frac{Umetrics_k / Umetrics}{Employees_k / Employees}$$

where $Umetrics_k$ is the number of Umetrics students that started their first job after graduation in industry k; $Umetrics$ is the total number of Umetrics students we observe entering the labor force; $Employees_k$ is the total number of employees in industry k (measured using aggregate employment from the LBD); and $Employees$ is total employment in the economy. To ensure that we observe sufficient numbers of job entries to compute meaningful differences across industries, we pool job entries across all currently available years of Umetrics data. We use employment shares by industry in the year 2010 as the scaling factor. Higher values of the index indicate a higher demand for research-trained students. A value of the HCI Index greater than 1 for industry k means that industry k attracts a higher share of research-trained first-time employees than its share of all employees in the economy. Industries that rely heavily on innovation and that are close to the technology frontier are likely to have higher values of the HCI Index. A novel feature of the HCI index is that it provides large variation in innovation intensity not only across manufacturing industries, like indices based on patents or R&D, but also across services industries, in which innovation is often not patented and hence not captured by standard measures of innovation used in the literature (Lerner and Seru, 2015).

In our context, we argue that a higher HCI index captures industries with more specialized and uncertain projects, and hence startups for which the wedge in information between the entrepreneur and potential lenders is higher.

[18] The pilot version of the project we can access includes information from 13 US universities for the period 2002-2014.

To validate our interpretation of the HCI index, we compute the standard deviation of the cumulative employment growth of startups within each three-digit NAICS industry at various horizons and then calculate its correlation with the index. Consistent with our interpretation, we find that the correlation between the standard deviation of employment growth and the HCI index is generally positive and increases over time. The correlation is 0.04 for two-year employment growth, 0.14 for two-year employment growth, and 0.21 for three-year employment growth. Thus, startups in industries with a higher HCI indeed grow at more varied rates over time, which is consistent with the hypothesis that their projects are more uncertain at the time that they obtain early financing.

Armed with the HCI index, we test whether the negative association between the index of SBA loans and startup employment growth is stronger among startups in high HCI industries. We repeat both sets of tests from Section V.A. (i.e., the sample splits into loans likely to come from the PLP and outside the PLP and into loans likely to come from the SBA Express Program and outside the SBA Express Program) for three separate ranges of the HCI index. The first group includes startups in industries for which HCI is below 0.25; the second group includes startups in industries in which HCI is between 0.25 and 2; and the third group includes startups in industries in which the HCI is higher than 2. This partition results in subsamples in the highest and lowest groups that are roughly equal in size.

Table 9 reports the results of estimating Equation (1) separately for each of the six groups of startups, based on whether founding employees live in zip codes in which they could have been exposed to loans through the PLP or not in each of the three partitions of the HCI index. Consistent with our predictions, in Panel A we find that a higher likelihood of receiving an SBA loan has a particularly strong and negative effect on employment growth among startups with founding employees who live in zip codes where the PLP is active and who found startups in high HCI industries. Focusing, for example, on employment growth over a four year horizon, we find that a one standard deviation increase in the index of SBA loans in the founding employees' home zip codes decreases employment growth by 3.3 percentage points. In the subsample of startups in industries with a low HCI value, the estimated association of SBA lending with growth is smaller in magnitude. For example, the coefficient estimate in the specification using four-year employment growth as the dependent variable is 22% higher among startups in the highest HCI industries compared to startups in the low HCI industries. Importantly, in Panel B of Table 9 we find that the association between the index of SBA loans and employment growth is consistently zero for any level of the HCI index, which suggests that the results in Panel A are not driven by unobserved characteristics of startups in industries with higher or lower values of HCI.[19]

In Table 10, we compare the growth of startups in industries with high, medium, and low values of the HCI index, based on whether their founding employees have exposure to the SBA Express program in their home zip codes or not. Consistent with the PLP results, we find negative selection in the samples of founding employees who have no exposure to SBA Express loans in the zip codes where they live. Negative selection is largest for startups in high-HCI industries, and the monotonic pattern across values of HCI is even more apparent than in the PLP subsample. The magnitude of the negative effects becomes insignificant among firms with the lowest values of the HCI index, for which information frictions are unlikely to be relevant.

Instead, we find no evidence that firms more likely to receive an SBA loan through the SBA Express program have lower employment growth than other startups in the same industries and zip codes. Moreover, there is no apparent pattern in the coefficients as we move across partitions of the HCI index – the positive association between the index of SBA loans and startup growth we documented in Panel A of Table 8 does not vary systematically across levels of HCI.[20]

Overall, these results provide an important independent corroboration of our interpretation of the negative relation between startup employment growth and the likelihood of SBA financing. Where information frictions are unlikely to be important, we find less negative patterns than where they are likely to be most relevant.

VI. Alternative Outcome Variables

Our analysis so far has used employment growth as a measure of startup performance. As we discussed in Section II, employment growth is likely to be the most relevant metric for startup firms. Nevertheless, as a final step, we discuss some evidence of how our measures of SBA lending correlate with other startup outcomes.

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[19] In Table A.3, we also confirm directly that there is no systematic relation between HCI and employment growth in specifications similar to those in Equation (1), which replace the index of SBA loans with HCI as the main covariate of interest.

[20] Note that under our interpretation of HCI as a measure of ex-ante uncertainty of startups projects, we do not predict any systematic pattern for this positive association across the values of HCI.

First, we re-examine the regressions from Sections IV and V using sales growth instead of employment growth as the outcome variable. A drawback to using sales as an outcome is that sales information is very frequently missing in the Census' Business Register. Sales can also be non-missing in some years, but missing in others for the same firm. Moreover observations of zero sales are common among startup firms, leading to large outliers in the distribution of growth rates (if we compute them as log changes). In these regressions, we have a drastically reduced sample size. The prevalence of missing data raises additional concerns to the extent that it is not random. Despite the far noisier environment, however, we find broadly consistent results. Startups that are more likely to receive an SBA loan significantly underperform startups of the same size in the same industries and zip codes. We continue to find evidence that the underperformance is concentrated in subsamples in which private lenders have weak incentives to screen, though the differences are less stark than those we uncover in Section V. We hesitate to draw any firm conclusions from this analysis (and particularly the sample splits) since it is unclear how the missing data interacts with our variables of interest.

We also consider growth in pay per employee to sharpen the interpretation of our results on employment growth. If, for example, some firms hire new employees at the expense of paying existing employees competitive rates, then the interpretation of higher employment growth would be more nuanced. In the subsamples of founding employees in which there is little scope for moral hazard on the part of lenders (no exposure to PLP; high exposure to the SBA Express program), we find no differences in the growth of pay per employee as a function of the likelihood a startup received an SBA loan, controlling for initial levels of pay per employee. Thus, there does not seem to be any systematic difference in the tradeoff startups make between paying wages to existing workers and hiring new workers. In the high moral hazard samples (high exposure to PLP; no exposure to SBA Express), we do see some evidence that startups that are more likely to receive an SBA loan have higher growth in pay per employee. The results are only (marginally) significant over a one (and sometimes two) year horizon. Moreover, they are small in magnitude (less than one percentage point). We are hesitant to over-interpret these weak results; however, they provide some tantalizing evidence that SBA loans to poor projects that result from lax screening do not facilitate startup growth, but do allow founding employees to extract slightly higher rents.

VII. Conclusion

We test whether government intervention in the market for startup lending through loan guarantees helps to correct a market failure, facilitating the entry of job-creating startups. We find that startups that are more likely to receive SBA-backed loans have lower employment growth over the first four years following founding. However, we find evidence that incentive misalignment in how loan screening and monitoring is performed appears to lead to funding of startups with worse-than-average prospects. We observe a negative relation between the likelihood of SBA funding and future employment growth when it is more likely that SBA lending comes through an expedited application program in which the SBA delegates decision-making authority fully to private lenders. We do not observe a negative relation when lending is more likely to come through an otherwise similar expedited application program in which moral-hazard incentives are low. Moreover, the extent of the negative relation between SBA lending and growth increases with the severity of information frictions regarding startup quality, which we measure using a novel index based on industry-level flows of highly-skilled, research-trained students into the labor market.

Our results suggest that the design of interventions into the entrepreneurial financing market that aim to correct market failures and incentivize commercial bank to lend to startups have important implications for their effectiveness. Separating fully decision-making authority from the cash flow consequences of the decision results in the funding of projects of lower-than-average quality, especially in highly uncertain industries. When the SBA reduces lenders' moral-hazard incentives, instead, the startups they finance perform as well as peers in the same industries and zip codes, or even better than them.

Note that the negative associations we document do not imply that government intervention is welfare destroying if it allows the financing of startups of lower-than-average quality, because the government's objective might not be to finance the best projects, but to spur any employment-creating and possibly value-creating venture, whatever the extent of this value. At the same time, some of the projects financed in settings in which the lending decision-making authority is fully separated from the cash flow consequences of the decision might have negative NPV once their risk is taken into account.

These results provide novel evidence of how government-guaranteed financing affects the growth and survival of new firms, especially in cases in which the high uncertainty of startup projects might determine a failure of private lending markets. Given the outsized role that the most successful startup firms play in job creation (relative to their share of the labor market), it is crucial to understand how different possible interventions in private lending markets can contribute to their survival and growth.

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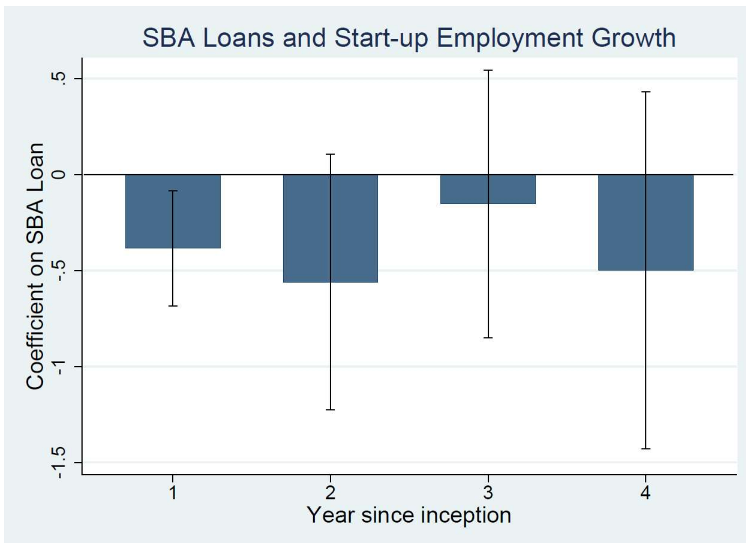
Figure 1: SBA Loans, Employment Growth and Startup Survival: Kauffman Firms Survey

This figure plots the estimated coefficients and 95% confidence intervals when regressing the cumulative start-up employment growth of the firms in the Kauffman Firm Survey on a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. In the top graph, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. In the bottom graph, the dependent variable is a dummy that equals 1 if the startup is still active in year 1, 2, 3, and 4 after inception, and 0 otherwise. In both graphs, the right hand side incudes a dummy variable that equals 1 if the startup obtained an SBA loan at inception (2004), and 0 otherwise; the logarithm of the number of employees in the startup at inception; a dummy variable that equals 1 if the principal owner of the startup is a woman, zero otherwise; a dummy variable that equals 1 if the principal owner of the startup is African-American, zero otherwise; a dummy variable that equals 1 if the principal owner is Asian, zero otherwise. All specifications include a full set of fixed effects for the census regions in which the startups operate, 2-digit NAICS codes, and the age group to which the principal owner belongs. Standard errors are clustered at the level of the industry to which the startup belongs.



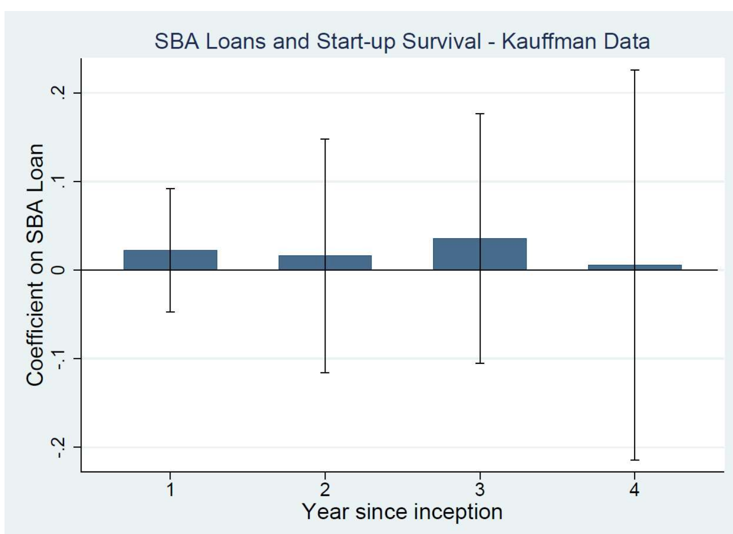


Table 1: Summary Statistics

SBA Loans measures the share of SBA loans per capital available in the zipcode. Log(HH Income) is the logarithm of average household income in the zipcode. Log (House Value) is the logarithm of average house value in the zip codel. Pct_Homeowners measures the percentage of households that are homeowners. Banking measures the relative size of the commerical banking sector in the zipcode, calculated as the ratio of employment in banking sector over total employment in the zip code. All the zipcode variables are measured at the zipcode where the founding employee resides. Age is the age of the worker. Female is an indicator variable that equals to 1 for female worker and zero otherwise. African-American is an indicator variable that equals to 1 for African workers and zero otherwise. Asian is an indicator variable that equals to 1 for Asian workers and zero otherwise.

Panel A. Geographic Distribution of Startups by Census Division

	N	%
East North Central	22,110	12.76
East South Central	7,570	4.37
Middle Atlantic	29,280	16.89
Mountain	12,910	7.45
New England	4,900	2.83
Pacific	29,940	17.28
South Atlantic	37,960	21.90
West North Central	8,720	5.03
West South Central	19,910	11.49

Panel B. Industry Distribution of Startups (2-Digit NAICS)

	N	%
Accommodation and Food Services	17,230	9.94
Administrative and Support and Waste Management and Remediation Services	9,790	5.65
Agriculture, Forestry, Fishing and Hunting	370	0.21
Arts, Entertainment and Recreation	3,120	1.80
Construction	16,610	9.59
Educational Services	2,710	1.57
Finance and Insurance	7,710	4.45
Health Care and Social Assistance	19,680	11.35
Information	2,230	1.29
Management of Companies and Enterprises	130	0.07
Manufacturing (NAICS 31)	1,290	0.74
Manufacturing (NAICS 32)	1,270	0.73
Manufacturing (NAICS 33)	2,520	1.45
Mining, Quarrying, and Oil and Gas Extraction	500	0.29
Other Services (except Public Administration)	14,930	8.61
Professional, Scientific, and Technical Services	26,730	15.43
Real Estate and Rental and Leasing	8,190	4.73
Retail Trade (NAICS 44)	17,410	10.05
Retail Trade (NAICS 45)	6,200	3.58
Transportation and Warehousing (NAICS 48)	4,940	2.85
Transportation and Warehousing (NAICS 49)	520	0.30
Utilities	110	0.06
Wholesale Trade	9,110	5.26

Panel C. Founding Employee Characteristics (N = 370,400)		
	Mean	Std. Dev.
SBA Loans p.c.	0.15	0.69
Log(Startup Employment)	1.19	0.74
Log(HH Income)	11.18	0.36
Log(House Value)	12.43	0.61
Pct Homeowners	0.66	0.17
Pct Workers Banking	0.01	0.02
Age	38.88	13.26
Female	0.49	0.50
African-American	0.06	0.23
Asian	0.11	0.32

Table 2: SBA Loans and Start-up Growth

This table reports the results for regressing the cumulative start-up empoyment growth on a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Index *SBA Loan* is the average of the SBA loans per capita available in the zipcodes in which the firms' employee resided in 2010, when all firms started their activities. Avg. *Log(HH Income)* is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. *Log (House Value)* is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. *Pct_Homeowners* measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. *Age* is the average age of the firm's employees. Share *Female* is the fraction of the firm's empoyees that are women. Share *African-American* is the fraction of the firm's employees that are African-American. Share *Asian* is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0079 ***	-0.0117 ***	-0.0104 ***	-0.0123 ***
	(-3.77)	(-4.43)	(-3.37)	(-3.58)
Avg. Log(HH Income)	-0.0105 **	-0.0142 **	-0.0131 *	-0.0191 **
	(-2.31)	(-2.43)	(-1.94)	(-2.39)
Avg. Log(House Value)	-0.0146 ***	-0.0169 **	-0.0183 **	-0.0132
	(-2.60)	(-2.31)	(-2.14)	(-1.36)
Avg. Pct. Homeowners	0.0059 ***	0.0078 **	0.0059	0.0099 **
	(2.15)	(2.16)	(1.45)	(2.04)
Avg. Pct. Workers Banking	-0.0017	-0.0013	0.0015	0.0025
	(0.99)	(0.58)	(0.57)	(0.84)
Avg. Age	-0.0428 ***	-0.0629 ***	-0.0775 ***	-0.0939 ***
	(-30.39)	(-35.11)	(-36.87)	(-38.61)
Share Female	0.0113 ***	0.0102 ***	0.0077 ***	0.0064 **
	(7.89)	(5.42)	(3.51)	(2.56)
Share African-American	0.0080 ***	0.0075 ***	0.0073 ***	0.0082 ***
	(4.89)	(3.48)	(2.80)	(2.71)
Share Asian	-0.0134 ***	-0.0159 ***	-0.0162 ***	-0.0211 ***
	(-9.12)	(-8.48)	(-7.44)	(-8.35)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	105,500
Adjusted R-squared	0.079	0.085	0.085	0.089

Table 3: SBA Loans and Start-up Survival

This table reports the results for predicting firms' likelihood to survive with a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is a dummy variable that equals 1 if the firm founded in 2010 is still operating in year 1, year 2, year 3, or year 4, and 0 otherwise. Index SBA Loan is the average of the SBA loans per capita available in the zipcodes in which the firms' employee resided in 2010, when all firms started their activities. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dep Var = Survival	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0011	-0.0002	-0.0004	-0.0003
	(-1.13)	(-0.18)	(-0.29)	(-0.20)
Avg. Log(HH Income)	-0.0001	0.0012	0.0007	-0.0007
	(-0.06)	(0.41)	(0.21)	(-0.21)
Avg. Log(House Value)	0.0027	0.0039	0.0037	0.0056
	(0.95)	(1.03)	(0.87)	(1.26)
Avg. Pct. Homeowners	0.0006	0.0020	0.0035 *	0.0058 ***
	(0.41)	(1.06)	(1.66)	(2.60)
Avg. Pct. Workers Banking	0.0002	-0.0001	-0.0013	-0.0001
	(0.19)	(-0.02)	(-1.06)	(-0.09)
Avg. Age	0.0058 ***	0.0130 ***	0.0148 ***	0.0167 ***
	(7.74)	(12.87)	(13.27)	(14.19)
Share Female	-0.0011	-0.0049 ***	-0.0054 ***	-0.0069 ***
	(-1.52)	(-4.86)	(-4.81)	(-5.76)
Share African-American	-0.0049 ***	-0.0109 ***	-0.0140 ***	-0.0170 ***
	(-5.98)	(-9.85)	(-11.42)	(-13.07)
Share Asian	0.0026 ***	0.0070 ***	0.0071 **	0.0016
	(3.24)	(6.55)	(5.88)	(1.23)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	173,300	173,300	173,300	173,300
Adjusted R-squared	0.013	0.015	0.017	0.022

Table 4: SBA Loans and Start-up Growth - Reduced Form Regression

This table reports the results for regressing the cumulative start-up empoyment growth on a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Pct Residents Banking is the average ratio of residents of the firms' employees zip code in 2010 that are employed in the banking sector. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4
Pct Residents Banking	-0.0114 ***	-0.0139 ***	-0.0200 ***	-0.0178 ***
	(-4.54)	(-4.29)	(-5.19)	(-4.02)
Avg. Log(HH Income)	-0.0053	-0.0084	-0.0030	-0.0110
	(-1.11)	(-1.37)	(-0.42)	(-1.32)
Avg. Log(House Value)	-0.0135 **	-0.0157 **	-0.0161 *	-0.0115
	(-2.40)	(-2.15)	(-1.88)	(-1.18)
Avg. Pct. Homeowners	0.0069 **	0.0095 ***	0.0068 *	0.0117 **
	(2.55)	(2.71)	(1.68)	(2.43)
Avg. Pct. Workers Banking	-0.0013	-0.0009	0.0022	0.0031
	(-0.79)	(-0.42)	(0.83)	(1.04)
Avg. Age	-0.0428 ***	-0.0629 ***	-0.0775 ***	-0.0939 ***
	(-30.36)	(-35.07)	(-36.85)	(-38.58)
Share Female	0.0113 ***	0.0101 ***	0.0076 ***	0.0063 **
	(7.85)	(5.39)	(3.47)	(2.53)
Share African-American	0.0081 ***	0.0076 ***	0.0074 ***	0.0083 ***
	(4.95)	(3.55)	(2.83)	(2.75)
Share Asian	-0.0130 ***	-0.0154 ***	-0.0153 ***	-0.0203 ***
	(-8.78)	(-8.16)	(-7.02)	(-8.01)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Year0 Emp Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	105,500
Adjusted R-squared	0.079	0.085	0.085	0.089

Table 5: SBA Loans and Start-up Growth - IV Approach

This table reports the results for regressing the cumulative start-up empoyment growth on a set of firm-level characteristics. Coefficients are computed using a two-stage least-square procedure. In Panel A (first-stage regression), the dependent variable is the firm-level index of likelihood of an SBA loan. In Panel B (second-stage regression), the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Avg. Pct. Residents Banking is the average ratio of residents of the firms' employees zip code in 2010 that are employed in the banking sector. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

Panel A: First-stage Regression	(1)	(2)	(3)	(4)
Dep Var = Index SBA Loan	Year 1	Year 2	Year 3	Year 4
Avg. Pct. Residents Banking	0.1220 ***	0.1230 ***	0.1240 ***	0.1240 ***
	(15.26)	(14.79)	(14.72)	(14.04)
Avg. Log(HH Income)	0.1980 ***	0.1980 ***	0.2050 ***	0.2000 ***
	(12.52)	(12.07)	(11.96)	(11.19)
Avg. Log(House Value)	0.0366 **	0.0359 **	0.0258	0.0303 ***
	(2.17)	(2.06)	(1.42)	(1.58)
Avg. Pct. Homeowners	-0.2700 ***	-0.2700 ***	-0.2720 ***	-0.2700 ***
	(-28.85)	(-28.02)	(-27.06)	(-25.82)
Avg. Pct. Workers Banking	0.0210 ***	0.0202 ***	0.0217 ***	0.0185 ***
	(4.35)	(3.93)	(3.88)	(3.71)
Avg. Age	-0.0012	-0.0010	-0.0004	-0.0023
	(-0.53)	(-0.43)	(-0.15)	(-0.81)
Share Female	-0.0021	-0.0026	-0.0034	-0.0024
	(-0.96)	(-1.09)	(-1.30)	(-0.81)
Share African-American	-0.0183 ***	-0.0180 ***	-0.0171 ***	-0.0187 ***
	(-8.95)	(-8.06)	(-7.05)	(-7.08)
Share Asian	0.0106 ***	0.0089 ***	0.0083 ***	0.0072 **
	(3.94)	(3.14)	(2.74)	(2.23)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	120,500
Adjusted R-squared	0.475	0.479	0.480	0.480

Panel B: Second Stage Regression	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0936 ***	-0.1130 ***	-0.1620 ***	-0.1430 ***
	(-4.43)	(-4.16)	(-4.90)	(-3.86)
Avg. Log(HH Income)	0.0132 *	0.0139	0.0301 **	0.0176
	(1.77)	(1.47)	(2.53)	(1.35)
Avg. Log(House Value)	-0.0101 *	-0.0117	-0.0120	-0.0072
	(-1.71)	(-1.32)	(-0.70)	(-0.70)
Avg. Pct. Homeowners	-0.0184 ***	-0.0210 **	-0.0372 ***	-0.0271 **
	(-2.83)	(-2.51)	(-3.59)	(-2.37)
Avg. Pct. Workers Banking	0.0006	0.0013	0.0057 **	0.0057 *
	(0.34)	(0.55)	(1.97)	(1.83)
Avg. Age	-0.0429 ***	-0.0630 ***	-0.0775 ***	-0.0942 ***
	(-30.22)	(-34.94)	(-36.45)	(-38.36)
Share Female	0.0111 ***	0.0098 ***	0.0071 ***	0.0060 **
	(7.63)	(3.16)	(3.16)	(1.79)
Share African-American	0.0064 ***	0.0056 **	0.0046 *	0.0056 *
	(3.77)	(2.51)	(1.69)	(1.79)
Share Asian	-0.0120 ***	-0.0144 ***	-0.0140 ***	-0.0193 ***
	(-7.81)	(-7.39)	(-6.15)	(-7.37)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	105,500
Adjusted R-squared	0.065	0.072	0.059	0.072

Table 6: SBA Loans and Start-up Growth - Placebo IV Approach

This table reports the results for regressing the cumulative start-up empoyment growth on a set of firm-level characteristics. Coefficients are computed using a two-stage least-square procedure. In Panel A (first-stage regression), the dependent variable is the firm-level index of likelihood of an SBA loan. In Panel B (second-stage regression), the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

Panel A: First-stage Regression	(1)	(2)	(3)	(4)
Dep Var = SBA Loans	Year 1	Year 2	Year 3	Year 4
Avg. Pct. Workers Banking	0.0268 ***	0.0261 ***	0.0277 ***	0.0246 ***
	(5.49)	(5.03)	(4.94)	(4.81)
Avg. Log(HH Income)	0.2770 ***	0.2780 ***	0.2850 ***	0.2800 ***
	(17.75)	(17.18)	(16.97)	(15.90)
Avg. Log(House Value)	0.0529 ***	0.0513 ***	0.0416 **	0.0460 **
	(3.09)	(2.91)	(2.26)	(2.38)
Avg. Pct. Homeowners	-0.2830 ***	-0.2830 ***	-0.2850 ***	-0.2820 ***
	(-29.29)	(-28.45)	(-27.58)	(-26.22)
Avg. Age	-0.0009	-0.0009	-0.0003	-0.0023
	(-0.43)	(-0.37)	(-0.14)	(-0.83)
Share Female	-0.0030	-0.0035	-0.0042	-0.0031
	(-1.33)	(-1.45)	(-1.63)	(-1.09)
Share African-American	-0.0187 ***	-0.0187 ***	-0.0178 ***	-0.0193 ***
	(-9.04)	(-8.23)	(-7.27)	(-7.24)
Share Asian	0.0169 ***	0.0152 ***	0.0146 ***	0.0135 ***
	(6.20)	(5.35)	(4.81)	(4.21)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	105,500
Adjusted R-squared	0.471	0.475	0.475	0.475

Panel B: Second Stage Regression	(1)	(2)	(3)	(4)
Dep Var = Growth	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0704	-0.0617	0.0428	0.0883
	(-1.09)	(-0.71)	(0.46)	(0.73)
Avg. Log(HH Income)	0.0068	-0.0003	-0.0283	-0.0473
	(0.37)	(-0.01)	(-1.03)	(-1.35)
Avg. Log(House Value)	-0.0113 *	-0.0143	-0.0205 **	-0.0178
	(-1.68)	(-1.64)	(-2.16)	(-1.56)
Avg. Pct. Homeowners	-0.0118	-0.0066	0.0211	0.0383
	(-0.64)	(-0.27)	(0.78)	(1.11)
Avg. Age	-0.0428 ***	-0.0630 ***	-0.0774 ***	-0.0937 ***
	(-30.29)	(-35.08)	(-36.73)	(-37.96)
Share Female	0.0112 ***	0.0100 ***	0.0080 ***	0.0067 ***
	(7.68)	(5.27)	(3.54)	(2.64)
Share African-American	0.0068 ***	0.0065 ***	0.0082 ***	0.0101 ***
	(3.36)	(2.47)	(2.70)	(2.66)
Share Asian	-0.0124 ***	-0.0152 ***	-0.0170 ***	-0.0225 ***
	(-6.60)	(-6.48)	(-6.50)	(-7.37)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	105,500
Adjusted R-squared	0.072	0.082	0.082	0.079

Table 7: SBA Loans, Preferred Lender Program, and Start-up Growth

This table reports the results from regressions on start-up growth for loans within the Preferred Lender Program (Panel A) and outside the Preferred Lender Program (Panel B). Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Index SBA Loan is the average of the SBA loans per capita available in the zipcodes in which the firms' employee resided in 2010, when all firms started their activities. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	Panel A: PLP = 1				Panel B: PLP = 0			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0297 ***	-0.0326 ***	-0.0309 ***	-0.0329 ***	0.0024	-0.0053	-0.0050	-0.0069
	(-11.54)	(-10.30)	(-8.53)	(-8.06)	(0.40)	(-0.71)	(-0.54)	(-0.66)
Avg. Log(HH Income)	-0.0163 ***	-0.0089	-0.0050	-0.0114	-0.0105	-0.0289 ***	-0.0254 **	-0.0254 **
	(-2.71)	(-1.13)	(-0.55)	(-1.09)	(-1.24)	(-2.68)	(-2.03)	(-2.03)
Avg. Log(House Value)	-0.0040	-0.0171 *	-0.0214 *	-0.0142	-0.0216 **	-0.0115	-0.0161	-0.0062
	(-0.55)	(-1.78)	(-1.90)	(-1.13)	(-2.00)	(-0.82)	(-0.99)	(-0.33)
Avg. Pct. Homeowners	0.0125 ***	0.0081 *	0.0044	0.0075	0.0050	0.0179 ***	0.0203 ***	0.0326 ***
	(3.56)	(1.77)	(0.82)	(1.20)	(0.96)	(2.73)	(2.59)	(3.47)
Avg. Pct. Workers Banking	-0.0007	-0.0020	0.0029	0.0047	-0.0006	0.0042	0.0053	0.0051
	(-0.32)	(-0.70)	(0.90)	(1.26)	(-0.18)	(1.03)	(1.03)	(0.81)
Avg. Age	-0.0441 ***	-0.0673 ***	-0.0837 ***	-0.1020 ***	-0.0375 ***	-0.0508 ***	-0.0607 ***	-0.0717 ***
	(-24.80)	(-29.46)	(-31.49)	(-33.67)	(-14.70)	(-15.73)	(-15.72)	(-15.96)
Share Female	0.0118 ***	0.0079 ***	0.0036	-0.0027 *	0.0105 ***	0.0149 ***	0.0150 ***	0.0095 **
	(6.58)	(3.40)	(1.29)	(-0.85)	(4.05)	(4.46)	(3.72)	(2.04)
Share African-American	0.0108 ***	0.0097 ***	0.0069 **	0.0078 **	0.0046	0.0057	0.0096 **	0.0050
	(5.12)	(3.44)	(2.01)	(1.98)	(1.64)	(1.59)	(2.21)	(1.00)
Share Asian	-0.0135 ***	-0.0170 ***	-0.0175 ***	-0.0236 ***	-0.0145 ***	-0.0140 ***	-0.0160 ***	-0.0170 ***
	(-7.75)	(-7.48)	(-6.72)	(-7.80)	(-4.88)	(-3.77)	(-3.56)	(-3.15)
Zip-code Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	106,200	92,700	81,900	71,800	50,900	43,900	38,600	33,700
Adjusted R-squared	0.090	0.093	0.093	0.097	0.106	0.119	0.115	0.124

Table 8: SBA Loans, SBA Express Program, and Start-up Growth

This table reports the results from regressions on start-up growth for loans within the SBA Express Program (Panel A) and outside the SBA Express Program (Panel B). Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Index SBA Loan is the average of the SBA loans per capita available in the zipcodes in which the firms' employee resided in 2010, when all firms started their activities. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	Panel A: SBA_Express = 1				Panel B: SBA_Express = 0			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	0.0241 ***	0.0223 ***	0.0258 ***	0.0260 ***	-0.0084 ***	-0.0129 ***	-0.0112 ***	-0.0147 ***
	(4.14)	(3.05)	(3.01)	(2.74)	(-3.64)	(-4.37)	(-3.20)	(-3.77)
Avg. Log(HH Income)	-0.0235 **	-0.0381 ***	-0.0287 *	-0.0346 *	-0.0065	-0.0068	-0.0026	-0.0043
	(-2.22)	(-2.78)	(-1.87)	(-1.93)	(-1.24)	(-0.98)	(-0.32)	(-0.45)
Avg. Log(House Value)	-0.0113	0.0045	-0.0062	0.0143	-0.0154 **	-0.0216 **	-0.0264 ***	-0.0301 **
	(-0.83)	(0.26)	(-0.31)	(0.64)	(-2.38)	(-2.48)	(-2.59)	(-2.57)
Avg. Pct. Homeowners	0.0099 **	0.0191 **	0.0166 *	0.0192 *	0.0040	0.0033	0.0002	0.0022
	(1.59)	(2.42)	(1.82)	(1.79)	(1.25)	(0.79)	(0.05)	(0.37)
Avg. Pct. Workers Banking	-0.0020	-0.0050	-0.0100 *	-0.0061	-0.0016	-0.0025	0.0030	0.0037
	(-0.52)	(-0.99)	(-1.74)	(-0.96)	(-0.81)	(-0.94)	(0.97)	(0.97)
Avg. Age	-0.0497 ***	-0.0666 ***	-0.0800 ***	-0.0934 ***	-0.0399 ***	-0.0608 ***	-0.0751 ***	-0.0926 ***
	(-17.09)	(-17.98)	(-17.97)	(-18.11)	(-24.24)	(-28.78)	(-30.38)	(-32.37)
Share Female	0.0122 ***	0.0097 **	0.0044	0.0035	0.0109 ***	0.0108 ***	0.0082 ***	0.0077 **
	(3.97)	(2.45)	(0.95)	(0.66)	(6.59)	(4.92)	(3.17)	(2.58)
Share African-American	0.0119 ***	0.0109 **	0.0091 *	0.0067	0.0058 ***	0.0051 **	0.0059 *	0.0060 *
	(3.58)	(2.44)	(1.73)	(1.10)	(3.05)	(2.03)	(1.95)	(1.71)
Share Asian	-0.0181 ***	-0.0153 ***	-0.0152 ***	-0.0217 ***	-0.0111 ***	-0.0160 ***	-0.0155 ***	-0.0214 ***
	(-5.58)	(-3.79)	(-3.24)	(-4.03)	(-6.52)	(-7.35)	(-6.04)	(-7.16)
Zip-code Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	48,100	42,400	37,700	33,200	109,000	94,200	82,800	72,300
Adjusted R-squared	0.100	0.107	0.107	0.110	0.087	0.091	0.093	0.097

Table 9: SBA Loans, Preferred Lender Program, HCI Index, and Start-up Growth

This table reports regressions on start-up growth. We split the sample by whether founding employees reside in zip codes with lending in the Preferred Lender Program or not and by value of the HCI index. HCI = High if HCI index is greater than or equal to 2. HCI = Medium if HCI index is between 0.25 and 2 and HCI = Low if HCI index is below 0.25. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Index SBA Loan is the average of the SBA loans per capita available in the zipcodes in which the firms' employee resided in 2010, when all firms started their activities. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

Panel A: PLP = 1	HCI = High				HCI = Medium				HCI =Low			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep Var = Emp. Growth	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0332 ***	-0.0325 ***	-0.0376 ***	-0.0334 ***	-0.0282 ***	-0.0334 ***	-0.0307 ***	-0.0335 ***	-0.0184 ***	-0.0201 ***	-0.0245 ***	-0.0274 ***
	(-5.99)	(-4.72)	(-4.51)	(-3.48)	(-8.40)	(-7.76)	(-6.16)	(-6.19)	(-3.02)	(-2.72)	(-2.84)	(-2.98)
Avg. Log(HH Income)	-0.0120	-0.0086	0.0074	-0.0211	-0.0193 **	-0.0064	-0.0018	-0.0047	-0.0062	-0.0078	-0.0205	0.0034
	(-0.83)	(-0.44)	(0.33)	(-0.77)	(-2.43)	(-0.62)	(-0.15)	(-0.34)	(-0.47)	(-0.46)	(-1.01)	(0.14)
Avg. Log(House Value)	-0.0037	-0.0131	-0.0480 *	-0.0115	-0.0079	-0.0249 **	-0.0273 *	-0.0259	-0.0056	-0.0223	0.0011	-0.0266
	(-0.20)	(-0.52)	(-1.66)	(-0.34)	(-0.82)	(-1.97)	(-1.81)	(-1.56)	(-0.35)	(-1.06)	(0.04)	(-0.89)
Avg. Pct. Homeowners	0.0170 **	0.0162	0.0093	0.0213	0.0137 ***	0.0047	0.0034	0.0042	0.0032	0.0112	0.0167	0.0086
	(2.04)	(1.45)	(0.70)	(1.38)	(2.93)	(0.77)	(0.47)	(0.50)	(0.37)	(1.03)	(1.29)	(0.58)
Avg. Pct. Workers Banking	-0.0038	-0.0081	-0.0011	-0.0116	-0.0018	-0.003	-0.002	0.0034	0.0054	0.0047	0.2080 **	0.0088
	(-0.67)	(-1.02)	(-0.11)	(-1.10)	(-0.62)	(-0.81)	(-0.50)	(0.70)	(0.87)	(0.65)	(1.98)	(0.95)
Avg. Age	-0.0547 ***	-0.0903 ***	-0.1140 ***	-0.1380 ***	-0.0415 ***	-0.0629 ***	-0.0761 ***	-0.0928 ***	-0.0444 ***	-0.0537 ***	-0.0668 ***	-0.0818 ***
	(-12.83)	(-15.59)	(-16.39)	(-16.62)	(-17.07)	(-19.48)	(-20.30)	(-22.25)	(-9.48)	(-9.38)	(-9.76)	(-10.17)
Share Female	0.0076 *	-0.0016	-0.0094	-0.0111	0.0126 ***	0.0099 ***	0.0073 *	0.0046	0.0127 ***	0.0111 *	0.0045	0.0059
	(1.84)	(-0.29)	(-1.38)	(-1.42)	(5.02)	(2.97)	(1.89)	(-1.04)	(2.77)	(1.93)	(0.63)	(0.73)
Share African-American	0.0071	0.0034	0.0064	0.0024	0.0138 ***	0.0143 ***	0.0075	0.0100	0.0053	0.0023	0.0094	0.0158 *
	(1.23)	(0.40)	(0.63)	(0.21)	(4.83)	(3.80)	(1.63)	(1.04)	(1.10)	(0.35)	(1.20)	(1.68)
Share Asian	-0.0116 **	-0.0126 *	-0.0114	-0.0116	-0.0162 ***	-0.0227 ***	-0.0253 ***	-0.0342 ***	-0.0128 ***	-0.0166 ***	-0.0128 **	-0.0172 ***
	(-2.50)	(-1.92)	(-1.43)	(-1.26)	(-6.60)	(-7.10)	(-6.82)	(-8.13)	(-3.40)	(-3.63)	(-2.37)	(-2.70)
Zip-code Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Initial Size Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	21,400	18,600	16,400	14,400	62,200	54,300	48,000	42,000	22,600	19,900	17,600	15,400
Adjusted R-squared	0.075	0.085	0.078	0.084	0.097	0.099	0.102	0.106	0.108	0.116	0.111	0.126

Panel B: PLP = 0	HCI = High				HCI = Medium				HCI =Low			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep Var = Emp. Growth	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	0.0288	-0.0085	-0.0339	-0.0258	-0.0022	-0.0115	-0.0089	-0.0148	0.0077	0.0032	0.0001	0.0097
	(1.52)	(-0.35)	(-1.13)	(-0.74)	(-0.27)	(-1.07)	(-0.68)	(-0.95)	(0.47)	(-0.16)	(0.01)	(0.33)
Avg. Log(HH Income)	-0.0159	-0.0716 **	-0.0973 **	-0.1060 **	-0.0093	-0.0358 **	-0.0316 *	-0.0404 *	-0.0305	-0.0491 *	-0.0411	-0.0373
	(-0.62)	(-2.11)	(-2.24)	(-2.14)	(-0.78)	(-2.29)	(-1.74)	(-1.87)	(-1.41)	(-1.92)	(-1.31)	(-1.02)
Avg. Log(House Value)	0.0083	0.0594	0.0694	0.1040	-0.0197	-0.0064	0.0045	-0.0024	-0.0009	0.0327	0.0017	0.0059
	(0.24)	(1.22)	(1.16)	(1.62)	(-1.32)	(-0.33)	(0.20)	(-0.09)	(0.03)	(0.94)	(0.04)	(0.13)
Avg. Pct. Homeowners	-0.0008	0.0204	0.0408	0.0551	0.0066	0.0265 ***	0.0250 **	0.0250 *	0.0281 **	0.0419 **	0.0344 *	0.0590 **
	(-0.05)	(0.94)	(1.48)	(1.63)	(0.92)	(2.89)	(2.31)	(1.93)	(2.01)	(2.45)	(1.72)	(2.49)
Avg. Pct. Workers Banking	-0.0067	-0.0003	-0.0015	0.0011	0.0006	0.0062	0.0090	0.0072	-0.0072	0.0015	-0.0101	-0.0069
	(-1.02)	(-0.03)	(-0.12)	(0.08)	(0.13)	(1.05)	(1.20)	(0.73)	(-0.87)	(0.16)	(-0.83)	(-0.52)
Avg. Age	-0.0376 ***	-0.0644 ***	-0.0798 ***	-0.0866 ***	-0.0359 ***	-0.0446 ***	-0.0542 ***	-0.0673 ***	-0.0361 ***	-0.0508 ***	-0.0642 ***	-0.0596 ***
	(-4.61)	(-6.08)	(-6.10)	(-5.57)	(-9.94)	(-9.57)	(-9.56)	(-10.10)	(-5.17)	(-5.94)	(-6.41)	(-5.01)
Share Female	0.0195 ***	0.0149	0.0002	-0.0102	0.0113 ***	0.0216 ***	0.0235 ***	0.0258 ***	0.0105	0.0136	0.0122	0.0065
	(2.66)	(1.55)	(0.01)	(-0.71)	(2.94)	(4.34)	(3.93)	(3.69)	(1.48)	(1.51)	(1.10)	(0.49)
Share African-American	-0.0047	-0.0126	0.0049	-0.0144	0.0097 ***	0.0170 ***	0.0196 ***	0.0090	-0.0026	-0.0151 *	-0.0178	-0.0195
	(-0.47)	(-0.87)	(0.27)	(-0.72)	(2.52)	(3.27)	(3.13)	(1.26)	(0.37)	(-1.68)	(-1.64)	(-1.48)
Share Asian	-0.0043	0.0167	0.0290 *	0.0189	-0.0163 ***	-0.0174 ***	-0.0137 **	-0.0132	-0.0200 ***	-0.0133	-0.0299 ***	-0.0288 **
	(-0.43)	(1.27)	(1.73)	(0.94)	(-3.73)	(-3.12)	(-1.99)	(-1.59)	(-2.85)	(-1.54)	(-2.96)	(-2.41)
Zip-code Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Initial Size Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8,900	7,700	6,800	6,000	29,100	24,900	21,900	19,100	12,900	11,200	9,900	8,600
Adjusted R-squared	0.093	0.110	0.070	0.112	0.111	0.118	0.120	0.122	0.128	0.150	0.154	0.171

Table 10: SBA Loans, SBA Express Program, HCI Index, and Start-up Growth

This table reports regressions on start-up growth. We split the sample by whether founding employees reside in zip codes with lending in the SBA Express Program or not and by value of the HCI index. HCI = High if HCI index is greater than or equal to 2. HCI = Medium if HCI index is between 0.25 and 2 and HCI = Low if HCI index is below 0.25. In both panels, regressions are run on the firm-worker level. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. Index SBA Loan is the average of the SBA loans per capita available in the zipcodes in which the firms' employee resided in 2010, when all firms started their activities. Avg. Log(HH Income) is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. Log (House Value) is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. Pct_Homeowners measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. Age is the average age of the firm's employees. Share Female is the fraction of the firm's empoyees that are women. Share African-American is the fraction of the firm's employees that are African-American. Share Asian is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

SBA_Express = 0	HCI = High				HCI = Medium				HCI = Low			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep Var = Emp. Growth	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	-0.0159 ***	-0.0157 **	-0.0231 ***	-0.0192 **	-0.0063 **	-0.0131 ***	-0.0098 **	-0.0136 **	-0.0004	-0.0048	-0.0082	-0.0106
	(-3.24)	(-2.39)	(-2.88)	(-2.07)	(-1.99)	(-3.25)	(-2.02)	(-2.55)	(-0.07)	(-0.66)	(-0.97)	(-1.11)
Avg. Log(HH Income)	0.0071	0.0079	0.0040	-0.0152	-0.0124 *	-0.0122	-0.0087	-0.0091	0.0004	0.0036	0.0118	0.0126
	(0.54)	(0.43)	(0.19)	(-0.59)	(-1.75)	(-1.28)	(-0.79)	(0.69)	(0.03)	(0.23)	(0.63)	(0.56)
Avg. Log(House Value)	-0.0300 *	-0.0332	-0.0400	-0.0147	-0.0147 *	-0.0222 *	-0.0261 *	-0.0355 **	-0.0199	-0.0391 **	-0.0347	-0.0426
	(-1.79)	(-1.42)	(-1.45)	(-0.45)	(-1.67)	(-1.92)	(-1.89)	(-2.26)	(-1.34)	(-2.00)	(-1.48)	(-1.58)
Avg. Pct. Homeowners	-0.0002	0.0020	0.0030	0.0128	0.0053	0.0030	0.0016	0.0030	0.0000	0.0025	-0.0007	-0.0048
	(-0.02)	(0.19)	(0.23)	(0.84)	(1.24)	(0.53)	(0.23)	(0.38)	(0.00)	(0.25)	(-0.06)	(-0.34)
Avg. Pct. Workers Banking	-0.0052	-0.0065	-0.0037	-0.0179 *	-0.0032	-0.0049	-0.0011	0.0035	0.0010	-0.0016	0.0136	0.0080
	(-1.07)	(-0.98)	(-0.42)	(-1.79)	(-1.14)	(-1.35)	(-0.28)	(0.64)	(0.19)	(-0.26)	(1.60)	(1.02)
Avg. Age	-0.0467 ***	-0.0826 ***	-0.1030 ***	-0.1280 ***	-0.0375 ***	-0.0563 ***	-0.0690 ***	-0.0836 ***	-0.0370 ***	-0.0488 ***	-0.0579 ***	-0.0723 ***
	(-11.35)	(-14.65)	(-15.23)	(-15.83)	(-16.45)	(-18.88)	(-19.73)	(-20.89)	(-8.45)	(-9.06)	(-8.84)	(-9.26)
Share Female	0.0091 **	0.0026	0.0004	-0.0004	0.0124 ***	0.0133 ***	0.0107 ***	0.0103 **	0.0102 **	0.0109 *	0.0022	0.0009
	(2.28)	(0.49)	(0.06)	(-0.06)	(5.18)	(4.18)	(2.87)	(2.40)	(2.39)	(1.96)	(0.33)	(0.12)
Share African-American	0.0008	0.0034	0.0078	0.0021	0.0874 ***	0.0109 ***	0.0090 **	0.0096 *	-0.0027	-0.0149 **	-0.0074	-0.0021
	(0.16)	(0.47)	(0.89)	(0.21)	(3.35)	(3.14)	(2.11)	(1.93)	(-0.6)	(-2.41)	(-1.05)	(-0.24)
Share Asian	-0.0101 ***	-0.0083	-0.0050	-0.0039	-0.0143 ***	-0.0210 ***	-0.0226 ***	-0.0318 ***	-0.0118 ***	-0.0177 ***	-0.0122 **	-0.0182 ***
	(-2.27)	(-1.3)	(-0.65)	(-0.43)	(-5.93)	(-6.82)	(-6.17)	(-7.44)	(-3.19)	(-3.84)	(-2.25)	(-2.80)
Zip-code Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Initial Size Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	21,700	18,600	16,300	14,300	62,700	54,200	47,600	41,500	24,500	21,400	18,800	16,400
Adjusted R-squared	0.069	0.079	0.077	0.083	0.089	0.090	0.092	0.097	0.109	0.114	0.123	0.124

SBA_Express = 1	HCI = High				HCI = Medium				HCI = Low			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep Var = Emp. Growth	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Index SBA Loan	0.0263 *	0.0344	0.0335	0.0313	0.0201 **	0.0185 *	0.0184	0.0206	0.0288 *	0.0167	0.0302	0.0293
	(1.68)	(1.59)	(1.27)	(1.05)	(2.57)	(1.79)	(1.58)	(1.53)	(1.94)	(0.97)	(1.41)	(1.23)
Avg. Log(HH Income)	-0.0092	-0.0306	-0.0110	-0.0464	-0.0204	-0.0321 *	-0.0201	-0.0271	-0.0201	-0.0235	-0.0223	-0.0372
	(-0.31)	(-0.83)	(-0.23)	(-0.80)	(-1.45)	(-1.73)	(-0.99)	(-1.11)	(-0.77)	(-0.73)	(-0.55)	(-0.83)
Avg. Log(House Value)	-0.0456	0.0041	-0.0430	0.0313	-0.0129	-0.0189	-0.0106	0.0133	-0.0034	0.0296	0.0345	0.0670
	(-1.24)	(0.09)	(-0.70)	(0.45)	(-0.70)	(-0.08)	(-0.40)	(0.43)	(-0.10)	(0.67)	(0.64)	(1.11)
Avg. Pct. Homeowners	0.0243	0.0122	0.0068	0.0354	0.0056	0.0205 **	0.0142	0.0094	0.0161	0.0323	0.0356	0.0468 *
	(1.38)	(0.53)	(0.23)	(1.00)	(0.68)	(1.99)	(1.19)	(0.43)	(1.02)	(1.60)	(1.42)	(1.67)
Avg. Pct. Workers Banking	-0.0149 *	-0.0230 **	-0.0258 *	-0.0126	0.0032	-0.0028	-0.0092	-0.0100	-0.0074	-0.0106	-0.0225	-0.0136
	(-1.75)	(-1.97)	(-1.92)	(-0.88)	(0.54)	(-0.41)	(-1.08)	(-0.99)	(0.74)	(-0.82)	(-1.48)	(-0.82)
Avg. Age	-0.0527 ***	-0.0730 ***	-0.0907 ***	-0.1050 ***	-0.0462 ***	-0.0646 ***	-0.0733 ***	-0.0868 ***	-0.0449 ***	-0.0545 ***	-0.0668 ***	-0.0756 ***
	(-6.15)	(-6.35)	(-6.53)	(-6.31)	(-11.32)	(-12.13)	(-11.71)	(-11.71)	(-5.57)	(-5.49)	(-5.79)	(-5.74)
Share Female	0.0098	-0.0002	-0.0237 *	-0.0310 **	0.0132 ***	0.0171 ***	0.0178 ***	0.0198 **	0.0059	0.0154	0.0202 *	0.0261 *
	(1.20)	(-0.01)	(-1.78)	(-2.00)	(2.99)	(2.93)	(2.62)	(2.57)	(0.73)	(1.55)	(1.65)	(1.89)
Share African-American	0.0032	-0.0114	-0.0033	0.0157	0.0157 ***	0.0182 ***	0.0131 *	0.0069	-0.0004	-0.0047	-0.0172	-0.0051
	(0.27)	(-0.71)	(-0.19)	(0.77)	(3.54)	(3.08)	(1.87)	(0.85)	(-0.04)	(-0.44)	(-1.35)	(-0.33)
Share Asian	-0.0066	-0.0014	0.0104	-0.0133	-0.0200 ***	-0.0210 ***	-0.0189 ***	-0.0234 ***	-0.0132 *	-0.0119	-0.0347 ***	-0.0307 ***
	(-0.60)	(-0.10)	(0.59)	(-0.63)	(-4.33)	(-3.58)	(-2.82)	(-2.91)	(-1.80)	(-1.35)	(-3.38)	(-2.64)
Zip-code Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Start-up Initial Size Fixed Eff	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8,700	7,600	6,800	6,000	28,500	25,000	22,300	19,600	10,900	9,700	8,600	7,600
Adjusted R-squared	0.083	0.112	0.069	0.088	0.107	0.110	0.120	0.114	0.122	0.143	0.115	0.142

Table A.1: Comparing the Preferred Lender Program (PLP) and SBA Express Program

The table below runs a comparative analysis of important characteristics of two SBA loan programs, that is, the PLP program and the SBA Express program. The analysis is based on the *SBA Standard Operating Procedure* (SOP) number 50 10 5(C), which was approved in October 2010, and is available online at the following address: https://www.sba.gov/sites/default/files/sops/serv_sops_50105c_loan_0.pdf. The main differences are as follows: (a) Guarantee: the guarantee for PLP loans can be up to 85% of the loan amount (75% for loans above $150,000). For SBA Express loans, it can be at most 50%. (b) Credit Decision: PLP lenders are fully delegated by the SBA in making the credit decision; SBA lenders are ultimately delegated to make the decision, but the SBA imposes detailed requirements lenders must follow. First, SBA lenders cannot conduct their assessment with methods that differ from other loans they make outside the SBA program. Second, they must document and explain in detail the methods they use to assess the quality of borrowers, including their statistical procedure, and explain why the methods are reliable. Third, SBA Express lenders must verify the existence and quality of collateral whenever needed, and need to require collateral if they do so for other loans outside the SBA program. Finally, the SBA steps in to review any early loan defaults for loans made by the lender. (c) Screening of Lender: PLP lenders provide crucial information regarding their monitoring and screening ability themselves to the SBA, and the SBA evaluates this information and decides whether to extend PLP status. SBA Express lenders, instead, let the SBA investigate and collect the needed information independently. (d) Renewal of Lender Status: PLP status renewal starts just before its expiration, and the status can be extended temporarily if renewal procedures are not complete. SBA Express status renewal starts months before its expiration, and cannot be extended beyond expiration unless a renewal decision is made by the SBA.

	PLP	**SBA EXPRESS**
Guarantee	SOP 50 10 5(C), Subpart B, page 128 Maximum Guaranty Amount Standard 7(a)/CLP/PLP loans: $3,750,000; Percentage: 85% for loans of $150,000 or less. 75% for loans over $150,000.	SOP 50 10 5(C), Subpart B, page 128 Maximum Guaranty Amount SBA Express Loans: $3,750,000-See Note 2; Percentage: 50% Note 2: The guaranteed amount of multiple loans counts toward the $3.75 million maximum guaranty that may be outstanding at any one time.
Credit Decision	SOP 50 10 5(C), Subpart A, page 31 (2) Credit Analysis SBA has authorized PLP lenders to make the credit decision without prior SBA review. The lender must perform a thorough and complete credit analysis of the applicant, establish that the loan is of such sound value as to reasonably assure repayment and document its analysis in the loan file.	SOP 50 10 5(C), Subpart A, page 43 (2) Credit Analysis (a)SBA has authorized SBA Express lenders to make the credit decision without prior SBA review. The credit analysis must demonstrate that there is a reasonable assurance of repayment. The lender is required to use appropriate, prudent and generally accepted industry credit analysis processes and procedures (which might include credit scoring), and these procedures must be generally consistent with those used for their similarly sized non-SBA guaranteed commercial loans. Lenders that do not use credit scoring for their similarly sized non-SBA guaranteed commercial loans may not use credit scoring for SBA Express. Lenders must validate (and document) with appropriate statistical methodologies that their credit analysis procedures are predictive of loan performance, and they must provide that documentation to SBA upon request. In addition, the credit scoring results must be documented in each loan file and available for SBA review. […] (c) The credit decision, including how much to factor in a past bankruptcy or whether to require

		an equity injection, is left to the business judgment of the lender. Also, if the lender requires an equity injection and, as part of its standard processes for non-SBA guaranteed loans verifies the equity injection, it must do so for SBA Express loans. (Lenders must adhere to the requirement that owners of 20% or more must inject equity into the business above certain thresholds. […] While the credit decision is left to the business judgment of the lender, early loan defaults will be reviewed by SBA pursuant SOP 50-51.
Screening of lender	<u>SOP 50 10 5(C), Subpart A, page 23</u> 3. Process to obtain PLP status A lender must submit its request for PLP status to its local SBA office with a copy of the SLPC […]. (a)The lender's request should include: [List of registry pieces of information] (9) Personnel who will: (a) Be in charge of PLP loans for the lender and their experience with the lender, in the industry, and with SBA loans; and (b) Have PLPL loan approval authority; (10) Where and how PLP loans will be processed, closed, serviced and liquidated; […] (c) The SBA field office sends the lender's request and the field office's recommendation to the LTT (d) The LTT's Role: The LTT gathers the information relevant to a lender's participation request, including the field office's recommendation and the processing, servicing and liquidation centers' written opinions of the lender's ability to process, close, service and liquidate SBA loans, as applicable. The LTT performs an analysis, makes a recommendation and sends it to the appropriate SBA official who makes a decision and notifies the LTT. The LTT then informs the lender of SBA's decision.	<u>SOP 50 10 5(C), Subpart A, page 35</u> 3. Process to become a SBA Express Lender (a) A lender may send a written request to the Lender Transaction Team (LTT) […] (d) The LTT gathers the information relevant to a lender's participation request. The LTT performs an analysis, makes a recommendation and sends it to the appropriate SBA official who make a decision and notifies the LTT. The LTT informs the lender of SBA's decision.
Renewal lender status	<u>SOP 50 10 5(C), Subpart A, page 25</u> 4. Process of renewal of PLP Status (a)The LTT automatically starts the renewal process just prior to the expiration of a lender's PLP status. […] (g) Temporary Extension of PLP status If a lender's PLP status is expiring and SBA has not completed the renewal process, the LTT may extend a lender's PLP status for a short, interim period as determined by the D/OCRM, in consultation with the D/FA.	<u>SOP 50 10 5(C), Subpart A, page 37</u> 6. Renewals of SBA Express status (a)The LTT will automatically start the renewal process a few months prior to the expiration of a lender's SBA Express status. […]

Table A.2: SBA Loans and Start-up Growth and Survival -- Kauffman Data

This table reports the results for regressing the cumulative start-up employment growth on a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. *SBA Loan* is a dummy variable that equals 1 if the start up obtained a SBA loan at inception (2004), and 0 otherwise. *Log(Emp.Startup)* is the logarithm of the number of employees in the startup at inception. *Female Owner* is a dummy variable that equals 1 if the principal owner of the startup is a woman, zero otherwise. *African-American Owner* is a dummy variable that equals 1 if the principal owner of the startup is African-American, zero otherwise. *Asian Owner* is a dummy variable that equals 1 if the principal owner is Asian, zero otherwise. All specifications include a full set of fixed effects for the census regions in which the startups operate, 2-digit NAICS codes, and the age group to which the principal owner belongs. Standard errors are clustered at the level of the industry to which the startup belongs, and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4
SBA Loan	-0.3840 **	-0.5600 *	-0.1520	-0.4990
	(-2.65)	(-1.74)	(-0.45)	(-1.11)
Log(Emp.Startup)	-0.0150 ***	-0.0210 ***	-0.0173 ***	-0.0151 **
	(-5.84)	(-5.11)	(-3.97)	(-2.22)
Female Owner	-0.0941	-0.3570 **	-0.2270	-0.2550
	(-0.82)	(-2.25)	(-0.95)	(1.12)
African-American Owner	0.2670	0.9530	0.6930	1.0090
	(0.74)	(0.97)	(0.91)	(0.74)
Asian Owner	0.0191	0.0270	0.0101	0.1190
	(0.16)	(0.97)	(0.05)	(0.57)
Census-region Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Owner Age group Fixed Effect	Y	Y	Y	Y
Observations	856	701	571	472
Adjusted R-squared	0.003	0.025	0.008	0.003

	(1)	(2)	(3)	(4)
Dep Var = Survival	Year 1	Year 2	Year 3	Year 4
SBA Loan	0.0223	0.0161	0.0358	0.0056
	(0.66)	(0.25)	(0.53)	(0.05)
Log(Emp.Startup)	0.0016	0.0021 *	-0.0006	0.0002
	(1.42)	(1.97)	(-0.47)	(0.19)
Female Owner	-0.0170	-0.0383	-0.0190	-0.0285
	(-0.64)	(-1.05)	(-0.47)	(-0.78)
African-American Owner	-0.0648 *	-0.1120 **	-0.1690 ***	-0.1380 ***
	(-1.74)	(-2.20)	(-3.76)	(-2.95)
Asian Owner	0.0080	0.0645	0.1180 **	0.1310 ***
	(0.21)	(1.25)	(1.96)	(1.80)
Census-region Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Owner Age group Fixed Effect	Y	Y	Y	Y
Observations	1,057	1,057	1,057	1,057
Adjusted R-squared	0.017	0.026	0.024	0.035

Table A.3: HCI Index and Start-up Growth

This table reports the results for regressing the cumulative start-up empoyment growth on a set of firm-level characteristics. Coefficients are computed by estimating a linear specification by ordinary least squares. In each column, the dependent variable is the logarithm of cumulative employment growth in year 1, 2, 3, and 4. *HCI Index* is the value of the Human-Capital Intensity Index for the NAICS 3 industry to which the startup belongs. Avg. *Log(HH Income)* is the average of the logarithm of the median household income in 2010 across the same zipcodes. Avg. *Log (House Value)* is the average of the logarithm of the median house value in 2010 in the zip codes. Avg. *Pct_Homeowners* measures the average percentage of households that are homeowners in 2010 in the zip codes. Avg. Pct. Workers Banking measures the relative size of the commerical banking sector in the zipcodes, calculated as the average ratio of employment in the banking sector over total employment in 2010 the zip codes. Avg. *Age* is the average age of the firm's employees. Share *Female* is the fraction of the firm's empoyees that are women. Share *African-American* is the fraction of the firm's employees that are African-American. Share *Asian* is the fraction of the firm's employees that are Asian. All specifications include a full set of fixed effects for the zip codes in which the startups operate, 2-digit NAICS codes, and the number of employees in the founding year. Standard errors are clustered at the level of the firms' zip code and t-statistics are reported in parentheses. *, **, *** represents significant level at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dep Var = Employment Growth	Year 1	Year 2	Year 3	Year 4
HCI Index	-0.0111 **	-0.0050	-0.0080	-0.0020
	(-2.58)	(-0.88)	(-1.16)	(-0.26)
Avg. Log(HH Income)	-0.0125 **	-0.0174 ***	-0.0160 **	-0.0225 ***
	(-2.76)	(-2.96)	(-2.36)	(-2.84)
Avg. Log(House Value)	-0.0150 ***	-0.0175 **	-0.0187 **	-0.0138
	(-2.68)	(-2.40)	(-2.19)	(-1.42)
Avg. Pct. Homeowners	0.0080 ***	0.0108 ***	0.0088 **	0.0134 ***
	(2.95)	(3.11)	(2.18)	(2.80)
Avg. Pct. Workers Banking	-0.0019	-0.0016	0.0012	0.0022
	(-1.12)	(-0.72)	(0.46)	(0.74)
Avg. Age	-0.0427 ***	-0.0629 ***	-0.0774 ***	-0.0939 ***
	(-30.34)	(-35.07)	(-36.82)	(-38.55)
Share Female	0.0114 ***	0.0102 ***	0.0078 ***	0.0064 **
	(7.92)	(5.45)	(3.54)	(2.58)
Share African-American	0.0081 ***	0.0077 ***	0.0075 ***	0.0084 ***
	(4.98)	(3.58)	(2.88)	(2.78)
Share Asian	-0.0137 ***	-0.0162 ***	-0.0164 ***	-0.0213 ***
	(-9.28)	(-8.60)	(-7.55)	(-8.43)
Zip-code Fixed Effect	Y	Y	Y	Y
NAICS2 Fixed Effect	Y	Y	Y	Y
Start-up Initial Size Fixed Effect	Y	Y	Y	Y
Observations	157,100	136,500	120,500	105,500
Adjusted R-squared	0.079	0.085	0.085	0.089